

Lesson 14: Purposeful model selection

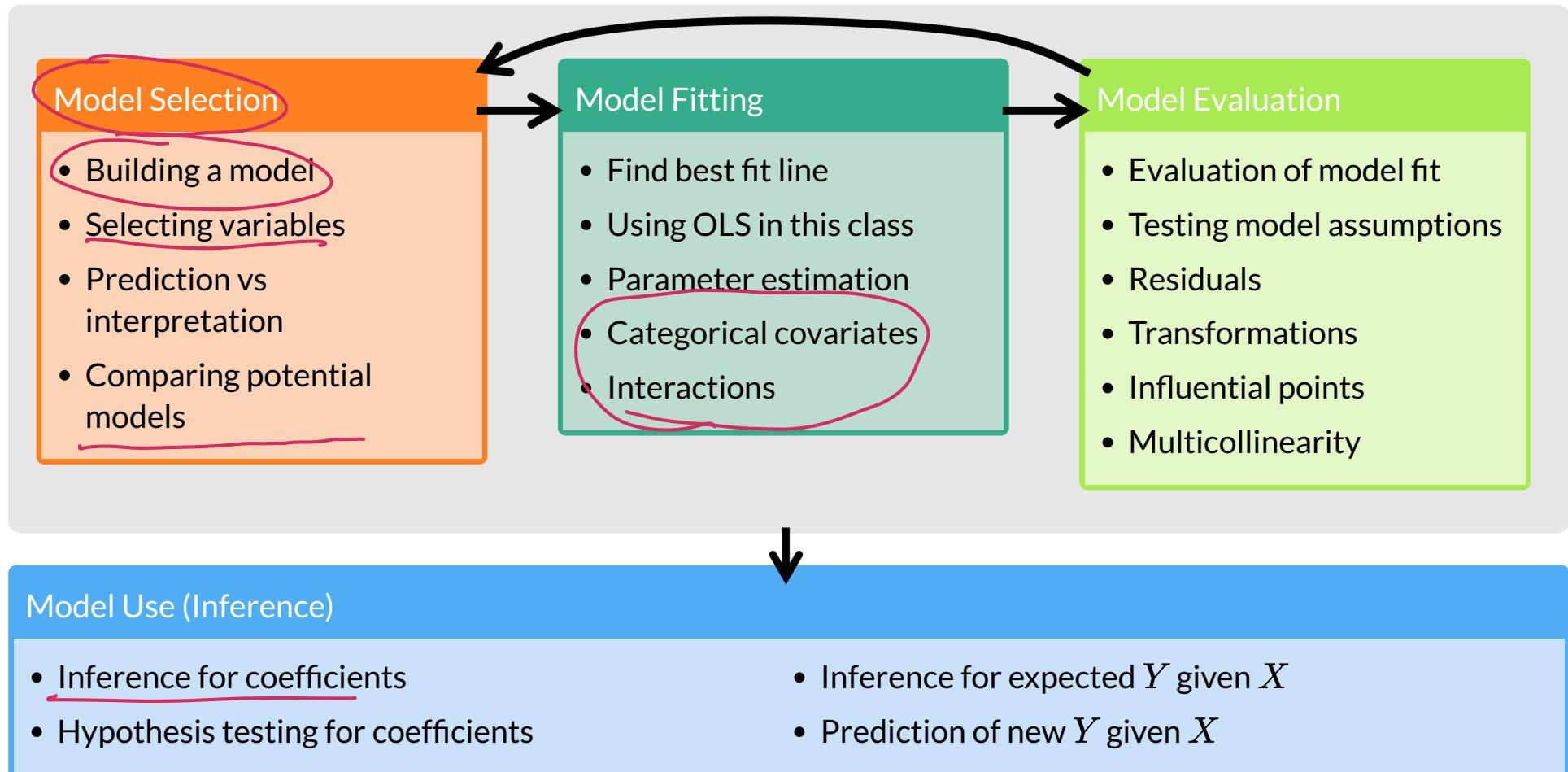
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2025-02-26

Learning Objectives

1. Understand the overall steps for purposeful selection as a model building strategy
2. Apply purposeful selection to a dataset using R
3. Use different approaches to assess the linear scale of continuous variables in ~~logistic~~ regression

Regression analysis process



Learning Objectives

1. Understand the overall steps for purposeful selection as a model building strategy
2. Apply purposeful selection to a dataset using R
3. Use different approaches to assess the linear scale of continuous variables in logistic regression

“Successful modeling of a complex data set
is part science, part **statistical methods**,
and part experience and common sense.”

Hosmer, Lemeshow, and Sturdivant Textbook, pg. 101

Overall Process

0. Exploratory data analysis
1. Check unadjusted associations in simple linear regression
2. Enter all covariates in model that meet some threshold
 - One textbook suggest $p < 0.2$ or $p < 0.25$: great for modest sized datasets
 - PLEASE keep in mind sample size in your study
 - Can also use magnitude of association rather than, or along with, p-value
3. Remove those that no longer reach some threshold
 - Compare magnitude of associations to unadjusted version (univariable)
4. Check scaling of continuous and coding of categorical covariates
5. Check for interactions
6. Assess model fit
 - Model assumptions, diagnostics, overall fit

Process with snappier step names

Pre-step: Exploratory data analysis (EDA)

Step 1: Simple linear regressions  / analysis

Step 2: Preliminary variable selection

Step 3: Assess change in coefficients

Step 4: Assess scale for continuous variables

Step 5: Check for interactions

Step 6: Assess model fit

Learning Objectives

1. Understand the overall steps for purposeful selection as a model building strategy
2. Apply purposeful selection to a dataset using R
3. Use different approaches to assess the linear scale of continuous variables in logistic regression

Pre-step: Exploratory data analysis

- The following slides are all reference until we get to Step 1
- We have covered exploratory data analysis in other classes and have completed it in our previous labs

Pre-step: Exploratory data analysis

- Things we have been doing over the quarter in class and in our project
- I will not discuss some of the methods mentioned in our lab and data management class
 - I am only going to introduce additional exploratory functions

A few things we can do:

- Check the data ✓
- Study your variables ✓
- Missing data? ✓
- Explore simple relationships and assumptions ✓

Pre-step: Exploratory data analysis: Check the data

- Get to know the potential values for the data
 - Categories
 - Units
- Then make sure the summary of values makes sense
 - If minimum or maximum look outside appropriate range
 - For example: a negative value for a measurement that is inherently positive (like population or income)

The screenshot shows the Gapminder Documentation page. At the top, there is a search bar, a logo, and navigation links for 'Donate', 'Resources', 'About', and 'Log in'. Below the header, a breadcrumb trail shows 'Home > Download the data > Documentation'. The main title 'Documentation' is in a large, bold, black font. A sub-section title 'Gapminder combines data from multiple sources into unique coherent time-series that can't be found elsewhere.' is followed by text explaining that most data is not good enough for detailed numeric analysis but is used to revolutionize people's worldview. It mentions filling gaps and improving data through a forum. Another section discusses current geographic boundaries and a link to more information. Below this, a paragraph explains how data is combined from various sources with links to complete calculations. It also notes that documentation is often incomplete. A list of data categories is provided, each with a link: Average age at 1st marriage (girls), Babies per woman (total fertility rate), Child Mortality Rate, under age five, GDP per capita in constant PPP dollars, Gini, HIV/AIDS, Income Mountains, Infant Mortality Rate, under age one, Legal slavery, Life Expectancy at Birth, Maternal mortality, Population, and World Health Chart, data sources. A note at the bottom states: 'This list only includes data that we have somehow modified or calculated ourselves. The complete list of data we use is [here](#)'.

<https://www.gapminder.org/data/documentation/>

Pre-step: Exploratory data analysis: Check the data

- Look at a summary for the raw data
- Typical use:

```
1 library(skimr)  
2 skim(gapm)
```

- Some `skim()` help

Pre-step: Exploratory data analysis: Check the data

- Look at a summary for the raw data
- Typical use:

```
1 library(skimr)  
2 skim(gapm)
```

- Some `skim()` help
- Note that `skim(gapm)` looks different because I had to create factors
- I am breaking down the `skim()` function into the categorical and continuous variables only because I want to show them on the slides

```
1 skim(gapm_sub1) %>% yank("factor")
```

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
four_regions	0	1.00	FALSE	4	Asi: 57, Afr: 54, Eur: 49, Ame: 35
income_levels1	1	0.99	FALSE	4	Hig: 56, Upp: 55, Low: 52, Low: 31
income_levels2	1	0.99	FALSE	2	Hig: 111, Low: 83

Pre-step: Exploratory data analysis: Check the data

```
1 skim(gapm_sub1) %>% yank("numeric")
```

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
CO2emissions	4	0.98	4.55	6.10	0.03	0.64	2.41	6.22	41.20	
ElectricityUsePP	58	0.70	4220.92	5964.07	31.10	699.00	2410.00	5600.00	52400.00	
FoodSupplykcPPD	27	0.86	2825.06	443.59	1910.00	2490.00	2775.00	3172.50	3740.00	
IncomePP	2	0.99	16704.45	19098.61	614.00	3370.00	10100.00	22700.00	129000.00	
LifeExpectancyYrs	8	0.96	70.66	8.44	47.50	64.30	72.70	76.90	82.90	
FemaleLiteracyRate	115	0.41	81.65	21.95	13.00	70.97	91.60	98.03	99.80	
WaterSourcePrct	1	0.99	84.84	18.64	18.30	74.90	93.50	99.07	100.00	
Latitude	0	1.00	19.11	23.93	-42.00	4.00	17.33	40.00	65.00	
Longitude	0	1.00	21.98	66.52	-175.00	-5.75	21.00	49.27	179.14	
population_mill	0	1.00	35.95	136.87	0.00	1.73	7.57	24.50	1370.00	

Poll Everywhere Question 1

In the following skim() output, what summaries might you flag?

```
1 skim(gapm_sub1) %>% yank("numeric")
```

Variable type: numeric

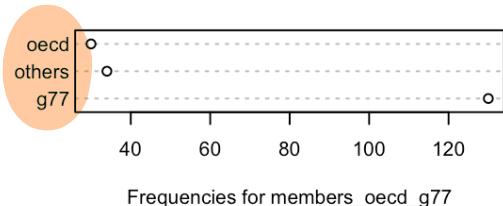
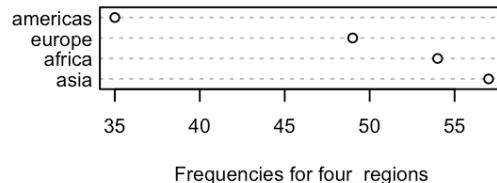
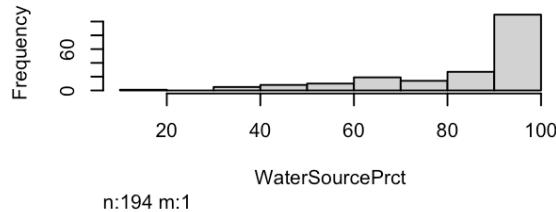
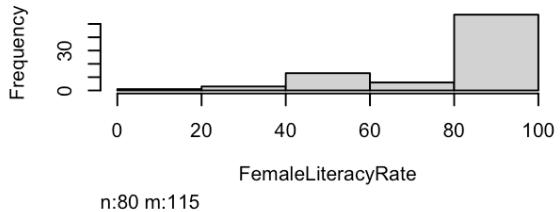
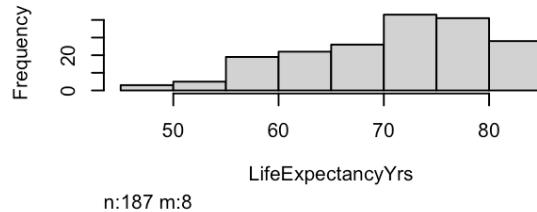
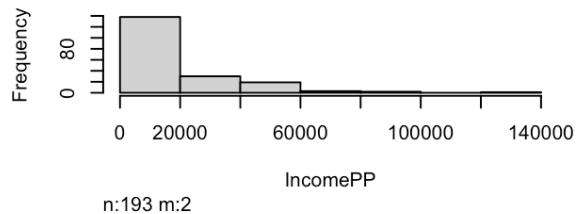
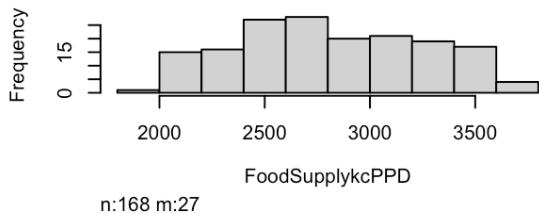
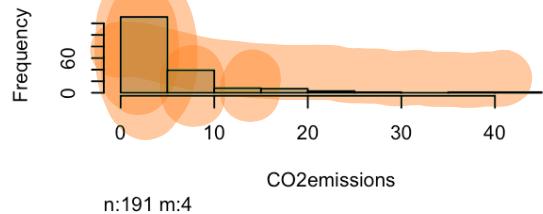
skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
CO2emissions	4	0.98	4.55	6.10	0.03	0.64	2.41	6.22	41.20	
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FoodSupplykcPPD	27	0.86	2825.06	443.59	1910.00	2490.00	2775.00	3172.50	3740.00	
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Longitude	0	1.00	21.98	66.52	-175.00	-5.75	21.00	49.27	179.14	
population_mill	0	1.00	35.95	136.87	0.00	1.73	7.57	24.50	1370.00	

Pre-step: Exploratory data analysis: Study your variables

- Started this a little bit in previous slide (`skim()`), but you may want to look at things like:
 - Sample size
 - Counts of missing data
 - Means and standard deviations
 - IQRs
 - Medians
 - Minimums and maximums
- Can also look at visuals
 - Continuous variables: histograms (in `skimr()` a little)
 - Categorical variables: frequency plots

Pre-step: Exploratory data analysis: Study your variables

```
1 library(Hmisc)
2 hist.data.frame(gapm %>% select(-Longitude, -Latitude, -eight_regions, -six_regions, -geo, -`World bank, 4 income groups 2017`, -country, -population, -`World bank region`, -ElectricityUsePP))
```



Poll Everywhere Question 2

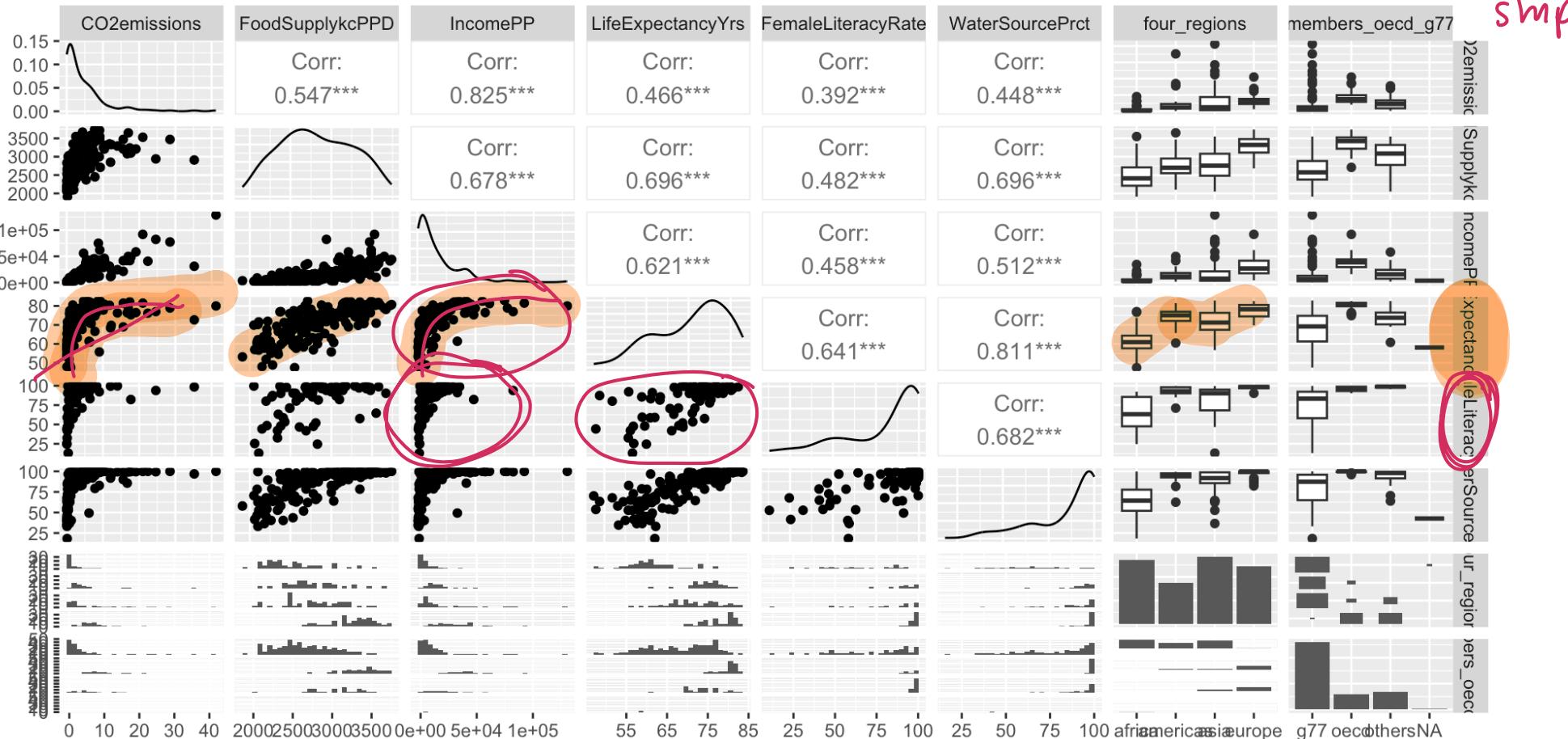
Question: What function might you use to visualize or summarize the frequencies of categorical variables?

Pre-step: Exploratory data analysis: Missing data

- Why are there missing data?
 - Which variables and observations should be excluded because of missing data?
 - Will I impute missing data?
-
- Unfortunately, we don't have time to discuss missing data more thoroughly
 - I will try to cover this topic more thoroughly in BSTA 513
-
- For the Gapminder dataset, we chose to use complete cases

Confounder relationships w/ exploratory var look @
 Pre-step / Step 1 : Explore simple relationships and assumptions main
 relationships w/ Y

```
1 gapm2 %>% ggpairs() # gapm2 is a new dataset with some variables selected
```



Poll Everywhere Question 3

Within the ggpairs output, is there a specific row/column that might be helpful when thinking about our outcome?



CO2emissions

FoodSupplykcPPD

IncomePP

LifeExpectancyYrs

FemaleLiteracyRate

WaterSourcePrct

four_regions

members_oecd_g77



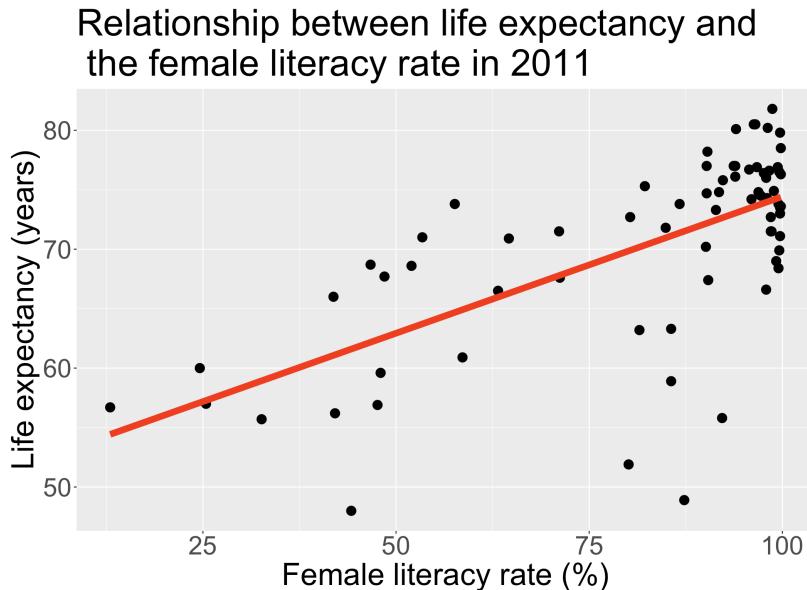
Step 1: Simple linear regressions / analysis

- For each covariate, we want to see how it relates to the outcome (without adjusting for other covariates)
- We can partially do this with **visualizations**
 - Helps us see the data we throw it into regression that makes assumptions (like our LINE assumptions)
 - `ggpairs()` can be a quick way to do it
 - `ggplot()` can make each plot
 - + `geom_boxplot()` to make boxplots by groups for categorical covariates
 - + `geom_jitter()` + `stat_summary()` to make non-overlapping points with group means for categorical covariates
 - + `geom_point()` to make scatterplots for continuous covariates
- We need to run **simple linear regression**
 - We're calling regression with multi-level categories "simple" even though there are multiple coefficients

Step 1: Simple linear regressions / analysis

- Let's think back to our Gapminder dataset
- Always good to start with our main relationship: life expectancy vs. female literacy rate
 - Throwback to Lesson 3 SLR when we first visualized and ran `lm()` for this relationship

```
1 model_FLR = lm(LifeExpectancyYrs ~ FemaleLiteracyRate, data = gapm_sub)
```



term	estimate	std.error	statistic	p.value
(Intercept)	51.438	2.739	18.782	0.000
FemaleLiteracyRate	0.230	0.032	7.141	0.000

t-test

Poll Everywhere Question 4

13:34 Wed Feb 26

Join by Web Polleverywhere.com/nickywakim275

"polleverywhere.com" is in full screen.
Swipe down to exit.

QR code

Look back at your Lesson 5 (SLR: More inference + Evaluation) notes.
What test can we run to show that Female Literacy Rate explains enough variation in Life Expectancy?

F-test with SLR model as full model and intercept model as reduced model  40%

F-test with multivariable model as full model and SLR model as reduced model 40%

F-test with multivariable model as full model and intercept model as reduced model 7%

t-test on the coefficient for Female Literacy Rate  13%

< 4 / 8 > |  Instructions Responses Correctness More Clear responses Exit

Powered by Poll Everywhere

pop model

$$LE = \beta_0 + \beta_1 FLR + \varepsilon$$

$$H_0: \beta_1 = 0$$

$$H_A: \beta_1 \neq 0$$

$$LE = \beta_0 + \varepsilon \text{ vs.}$$

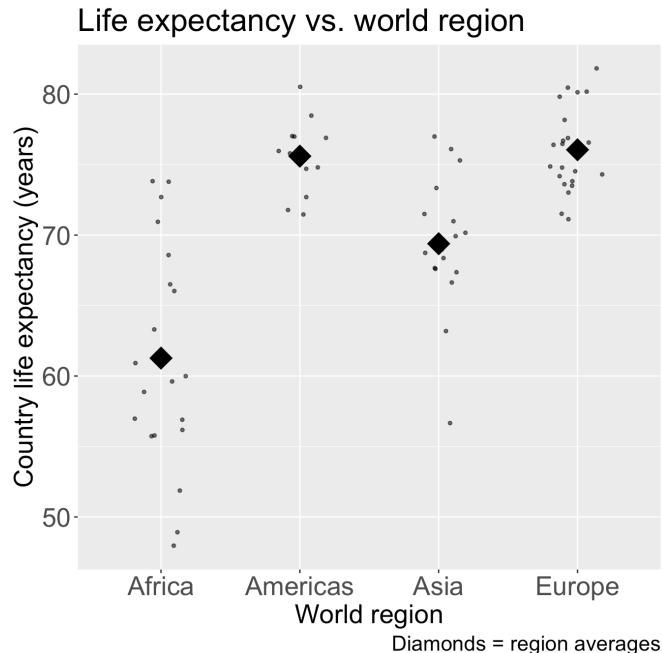
$$LE = \beta_0 + \beta_1 FLR + \varepsilon$$

Step 1: Simple linear regressions / analysis

- Let's do this with one other variable before I show you a streamlined version of SLR

```
1 model_WR = lm(lifeExpectancyYrs ~ four_regions, data = gapm_sub)
```

Code



```
1 anova(model_WR) %>% tidy() %>% gt() %>%
2   tab_options(table.font.size = 40) %>%
3   fmt_number(decimals = 3)
```

F-test only

term	df	sumsq	meansq	statistic	pvalue
four_regions	3.000	2,743.042	914.347	33.680	0.000
Residuals	68.000	1,846.077	27.148	NA	NA

- Recall from Lesson 5 (SLR: More inference + Evaluation):
 - `anova()` with one model name will compare the model (`model_WR`) to the intercept model

Step 1: Simple linear regressions / analysis

- If we do a good job visualizing the relationship between our outcome and each covariate, then we can proceed to a streamlined version of the F-test for each relationship
- Run `add1()` to add each variable one at a time and separately
- Output will include hypothesis test (using F-test) if coefficient(s) is 0 or not

```
1 intercept_model = gapm2 %>% lm(formula = LifeExpectancyYrs ~ 1)
2 add1(intercept_model, scope = ~FemaleLiteracyRate + C02emissions + IncomePP + four_regions +
3 WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77, test = "F")
```

Single term additions

Model:
LifeExpectancyYrs ~ 1

	Df	Sum of Sq	RSS	AIC	F value	Pr(>F)
<none>		4589.1	301.14			
FemaleLiteracyRate	1	1934.24	2654.9	263.74	50.9994	6.895e-10 ***
C02emissions	1	452.31	4136.8	295.67	7.6536	0.007241 **
IncomePP	1	1220.34	3368.8	280.89	25.3576	3.557e-06 ***
four_regions	3	2743.04	1846.1	241.58	33.6799	1.858e-13 ***
WaterSourcePrct	1	2988.20	1600.9	227.32	130.6592	< 2.2e-16 ***
FoodSupplykcPPD	1	1893.44	2695.7	264.84	49.1679	1.188e-09 ***
members_oecd_g77	2	1103.71	3485.4	285.34	10.9250	7.553e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$$\begin{aligned} \text{red: } LE &= \beta_0 + \varepsilon \\ \text{full: } LE &= \beta_0 + \beta_1 X + \varepsilon \end{aligned}$$

or $\begin{cases} \beta_1 I(-) \\ + \beta_2 I(-) \end{cases}$

cat

Step 2: Preliminary variable selection

- Identify candidates for your first multivariable model by performing an F-test on each covariate's SLR
 - Using p-values from previous slide
 - If the p-value of the test is less than 0.25, then consider the variable a candidate

- Candidates for first multivariable model
 - All clinically important variables (regardless of p-value)
 - Variables with univariate test with p-value < 0.25

F-test for SLR

- With more experience, you won't need to rely on these strict rules as much

Step 2: Preliminary variable selection

- From the previous p-values from the F-test on each covariate's SLR
 - Decision: we keep all the covariates since they all have a p-value < 0.25

```
1 add1(intercept_model, scope = ~ FemaleLiteracyRate + CO2emissions + IncomePP + four_regions +
2   WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77, test = "F")
```

Single term additions

Model:

LifeExpectancyYrs ~ 1

	Df	Sum of Sq	RSS	AIC	F value	Pr(>F)	
<none>		4589.1	301.14				
FemaleLiteracyRate	1	1934.24	2654.9	263.74	50.9994	6.895e-10	***
CO2emissions	1	452.31	4136.8	295.67	7.6536	0.007241	**
IncomePP	1	1220.34	3368.8	280.89	25.3576	3.557e-06	***
four_regions	3	2743.04	1846.1	241.58	33.6799	1.858e-13	***
WaterSourcePrct	1	2988.20	1600.9	227.32	130.6592	< 2.2e-16	***
FoodSupplykcPPD	1	1893.44	2695.7	264.84	49.1679	1.188e-09	***
members_oecd_g77	2	1103.71	3485.4	285.34	10.9250	7.553e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1							

Step 2: Preliminary variable selection

- Fit an initial model including any independent variable with p-value < 0.25 and clinically important variables

```
1 init_model = lm(LifeExpectancyYrs ~  
2 FemaleLiteracyRate +  
3 CO2emissions +  
4 IncomePP +  
5 four_regions +  
6 WaterSourcePrct +  
7 FoodSupplykcPPD +  
8 members_oecd_g77,  
9 data = gapm2)  
10  
11 tbl_regression(  
12 init_model,  
13 label = list(  
14 FemaleLiteracyRate ~ "Female literacy rate (%)",  
15 CO2emissions ~ "CO2 emissions",  
16 IncomePP ~ "Income (GDP per capita)",  
17 four_regions ~ "World region",  
18 WaterSourcePrct ~ "Access to improved water (%)",  
19 FoodSupplykcPPD ~ "Food supply (kcal PPD)",  
20 members_oecd_g77 ~ "Intergovernmental group"  
)) %>%  
22 as_gt() %>%  
23 tab_options(table.font.size = 26)
```

Characteristic	Beta	95% CI ¹	p-value
Female literacy rate (%)	0.00	-0.07, 0.07	>0.9
CO2 emissions	-0.29	-0.55, -0.02	0.037
Income (GDP per capita)	0.00	0.00, 0.00	0.019
World region			
Africa	—	—	
Americas	9.9	5.9, 14	<0.001
Asia	5.8	2.6, 9.0	<0.001
Europe	7.1	1.7, 13	0.010
Access to improved water (%)	0.14	0.01, 0.27	0.041
Food supply (kcal PPD)	0.01	0.00, 0.01	0.015
Intergovernmental group			
g77	—	—	
oecd	-0.33	-5.4, 4.8	0.9
others	0.33	-4.3, 4.9	0.9

¹ CI = Confidence Interval

Step 3: Assess change in coefficient

- This is where we start identifying covariates that we might remove

- I would start by using the p-value to guide me towards specific variables

- Female literacy rate, but that's our main covariate
- Intergovernmental group?
- Maybe water source percent?

- Some people will say you can use the p-value alone
 - I like to double check that those variables do not have a large effect on the other coefficients

Characteristic	Beta	95% CI ¹	p-value
Female literacy rate (%)	0.00	-0.07, 0.07	>0.9
CO2 emissions	-0.29	-0.55, -0.02	0.037
Income (GDP per capita)	0.00	0.00, 0.00	0.019
World region			
Africa	—	—	
Americas	9.9	5.9, 14	<0.001
Asia	5.8	2.6, 9.0	<0.001
Europe	7.1	1.7, 13	0.010
Access to improved water (%)	0.14	0.01, 0.27	0.041
Food supply (kcal PPD)	0.01	0.00, 0.01	0.015
Intergovernmental group			
g77	—	—	
oecd	-0.33	-5.4, 4.8	0.9
others	0.33	-4.3, 4.9	0.9

¹ CI = Confidence Interval

Step 3: Assess change in coefficient

- Very similar to the process we used when looking at confounders

- One variable at a time, we run the multivariable model  with and without a variable
 - We look at the p-value of the F-test for the coefficients of said variable
 - We look at the percent change for the coefficient ($\Delta\%$) of our **explanatory variable** (FLR in our example)
- General rule: We can remove a variable if...
 - p-value > 0.05 for the F-test of its own coefficients
 - AND change in coefficient ($\Delta\%$) of our explanatory variable is < 10%

F-test on dropping each covariate

- Function `drop1()`: If we put in our initial model, the function will remove each covariate and perform the respective F-test to test if the coefficients are 0 (null) or not (alternative).

```
1 drop1(init_model, test="F")
```

Single term deletions

Model:

LifeExpectancyYrs ~ FemaleLiteracyRate + CO2emissions + IncomePP +
four_regions + WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77

	Df	Sum of Sq	RSS	AIC	F value	Pr(>F)
<none>		999.20	211.38			
FemaleLiteracyRate	1	0.06	999.26	209.38	0.0034	0.95391
CO2emissions	1	74.63	1073.83	214.57	4.5559	0.03683 *
IncomePP	1	95.40	1094.60	215.95	5.8240	0.01883 *
four_regions	3	410.14	1409.34	230.14	8.3462	9.822e-05 ***
WaterSourcePrct	1	71.74	1070.94	214.37	4.3799	0.04053 *
FoodSupplykcPPD	1	102.06	1101.26	216.38	6.2305	0.01528 *
members_oecd_g77	2	1.79	1000.99	207.51	0.0546	0.94696

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

F-test

$\beta = 0$ vs $\beta \neq 0$

not sig p-val

$\Rightarrow \beta = 0$

$\beta_1 = \beta_2 = \beta_3 = 0$ vs

$\beta_1 \neq 0$ or $\beta_2 \neq 0$

or $\beta_3 \neq 0$

Testing for percent change ($\Delta\%$) in a coefficient

- Let's say we have X_1 and X_2 , and we specifically want to see if X_2 is a confounder for X_1 (the explanatory variable or variable of interest)
- If we are only considering X_1 and X_2 , then we need to run the following two models:
 - Fitted model 1 / reduced model (mod1): $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1$
 - We call the above $\hat{\beta}_1$ the reduced model coefficient: $\hat{\beta}_{1,\text{mod1}}$ or $\hat{\beta}_{1,\text{red}}$
 - Fitted model 2 / Full model (mod2): $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2$
 - We call this $\hat{\beta}_1$ the full model coefficient: $\hat{\beta}_{1,\text{mod2}}$ or $\hat{\beta}_{1,\text{full}}$

Calculation for % change in coefficient

$$\Delta\% = 100\% \cdot \frac{\hat{\beta}_{1,\text{mod1}} - \hat{\beta}_{1,\text{mod2}}}{\hat{\beta}_{1,\text{mod2}}} = 100\% \cdot \frac{\hat{\beta}_{1,\text{red}} - \hat{\beta}_{1,\text{full}}}{\hat{\beta}_{1,\text{full}}}$$

Step 3: Assess change in coefficient

- Let's try this out on members_oecd_g77
 - Display the ANOVA table with F-statistic and p-value

term	df.residual	rss	df	sumsq	statistic	p.value
LifeExpectancyYrs ~ FemaleLiteracyRate + CO2emissions + IncomePP + four_regions + WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77	61.000	999.201	NA	NA	NA	NA
LifeExpectancyYrs ~ FemaleLiteracyRate + CO2emissions + IncomePP + four_regions + WaterSourcePrct + FoodSupplykcPPD	63.000	1,000.988	-2.000	-1.787	0.055	0.947

- $\hat{\beta}_{FLR,full} = 0.002$, $\hat{\beta}_{FLR,red} = 0.0036$

$$\Delta\% = 100\% \cdot \frac{\hat{\beta}_{FLR,full} - \hat{\beta}_{FLR,red}}{\hat{\beta}_{FLR,full}} = 100\% \cdot \frac{0.002 - 0.0036}{0.002} = -74.41\%$$

- Based off the percent change, I would keep this in the model

Step 3: Assess change in coefficient (Reference only)

- Let's try this out on water source percent (even though the p-value was < 0.05)
 - Display the ANOVA table with F-statistic and p-value

term	df.residual	rss	df	sumsq	statistic	p.value
LifeExpectancyYrs ~ FemaleLiteracyRate + CO2emissions + IncomePP + four_regions + WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77	61.000	999.201	NA	NA	NA	NA
LifeExpectancyYrs ~ FemaleLiteracyRate + CO2emissions + IncomePP + four_regions + members_oecd_g77 + FoodSupplykcPPD	62.000	1,070.944	-1.000	-71.744	4.380	0.041

- $\hat{\beta}_{FLR,full} = 0.002, \hat{\beta}_{FLR,red} = 0.034$

$$\Delta\% = 100\% \cdot \frac{\hat{\beta}_{FLR,full} - \hat{\beta}_{FLR,red}}{\hat{\beta}_{FLR,full}} = 100\% \cdot \frac{0.002 - 0.034}{0.002} = -1561.06\%$$

- Based off the percent change (and p-value), I would keep this in the model

Poll Everywhere Question 5

13:58 Wed Feb 26

Join by Web PollEv.com/nickywakim275

Which of the following is/are an important inclusion rule for variables when we are model building?

Including variables that are clinical... *al Sig.* 0%

Including variables that are significant in the model 0%

Including variables that are confounders... 0%

All of the above 44%

A and B only 33%

B and C only 11%

A and C only 11%

Powered by  Poll Everywhere



Response	Percentage
Including variables that are clinical...	0%
Including variables that are significant in the model	0%
Including variables that are confounders...	0%
All of the above	44%
A and B only	33%
B and C only	11%
A and C only	11%

Step 3: Assess change in coefficient: Summary

- At the end of this step, we have a **preliminary main effects model**
- Where the variables are excluded that met the following criteria:
 - P-value > 0.05 for the F-test of its own coefficients
 - Change in coefficient ($\Delta\%$) of our explanatory variable is < 10%
- In our example, the **preliminary main effects model** (end of Step 3) was the same as the **initial model** (end of Step 2)
- Preliminary main effects model includes:
 - FemaleLiteracyRate
 - C02emissions
 - IncomePP
 - four_regions
 - members_oecd_g77
 - FoodSupplykcPPD
 - WaterSupplePct

Recap of Steps 1-3

- Pre-step: Exploratory data analysis
- Step 1: Simple linear regressions / analysis
 - Look at each covariate with outcome
 - Perform SLR for each covariate
- Step 2: Preliminary variable selection
 - From SLR, decide which variables go into the initial model
 - Use F-test to see if each covariate (on its own) explains enough variation in outcome
 - End with **initial model**
- Step 3: Assess change in coefficients
 - From the initial model at end of step 2, we take a variable out of the model if:
 - P-value > 0.05 for the F-test of its own coefficients
 - Change in coefficient ($\Delta\%$) of our explanatory variable is < 10%
 - End with **preliminary main effects model**

Learning Objectives

1. Understand the overall steps for purposeful selection as a model building strategy
2. Apply purposeful selection to a dataset using R
3. Use different approaches to assess the linear scale of continuous variables in logistic regression

Step 4: Assess scale for continuous variables

- We assume the linear regression model is linear for each continuous variable
- We need to assess linearity for continuous variables in the model
 - Do this through smoothed scatterplots that we introduced in Lesson 6 (SLR Diagnostics)
 - Residual plots (can be used in SLR) does not help us in MLR
 - Each term in MLR model needs to have linearity with outcome
- Three methods/approaches to address the violation of linearity assumption:
 - Approach 1: Categorize continuous variable
 - Approach 2: Fractional Polynomials
 - Approach 3: Spline functions
- Approach will depend on the covariate!!
- For our class, only implement Approach 1 or 2
- Model at the end of Step 4 is the main effects model

log-
outside of transformation

still run into issues
w/ interpretability

Step 4: Assess scale for continuous variables: Smoothed scatterplots

- Smoother scatterplots **only check linearity**, not addressing linearity issues
- Can also identify extreme observations
 - Again, just want to flag these values
 - Can influence the assessment of linearity when using fractional polynomials or spline functions
- Helps us decide if the continuous variable can stay **as is** in the model
 - **Problem:** if not linear, then we need to represent the variable in a new way (Approaches 1-3)

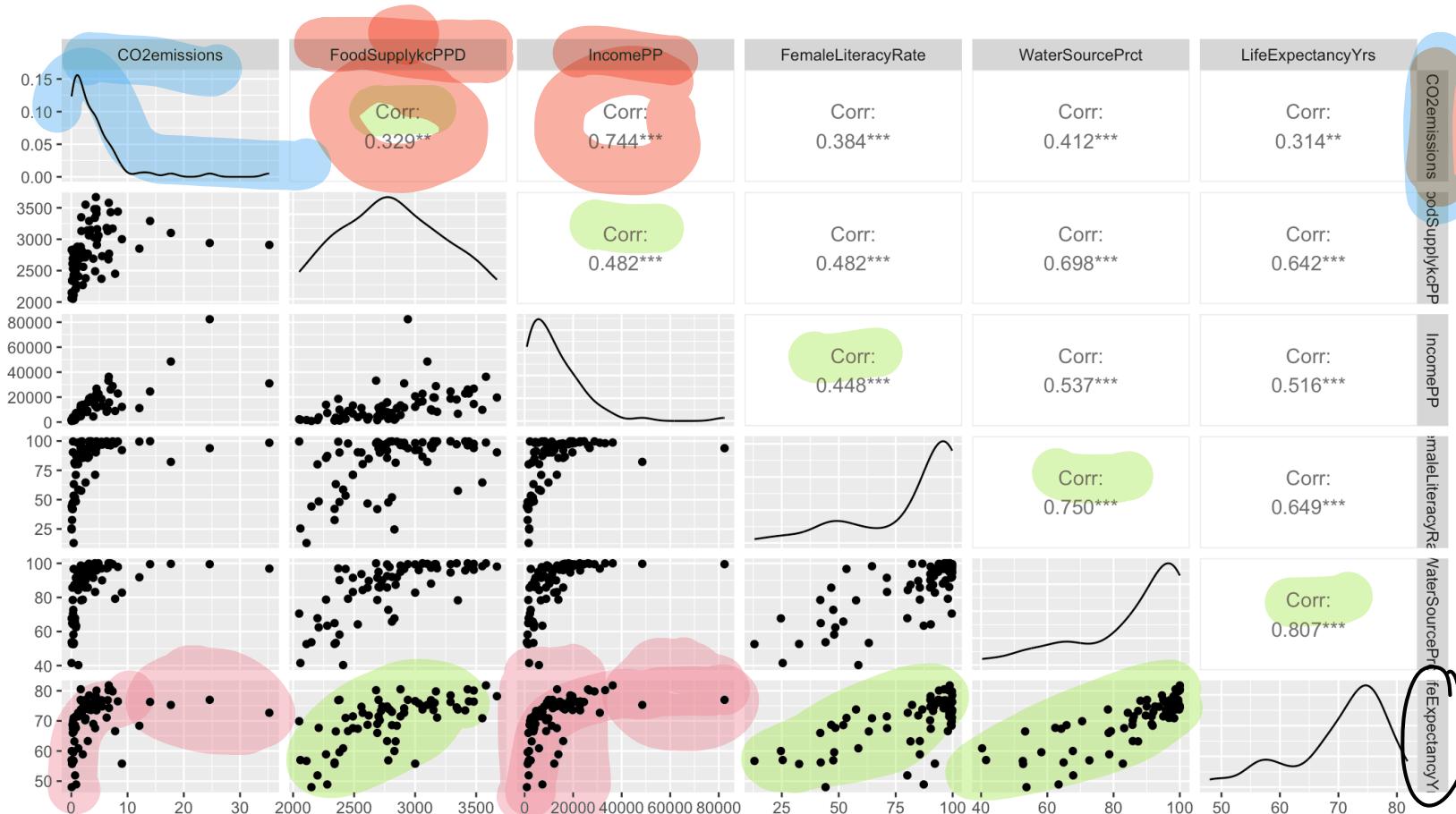
x^2

Step 4: Assess scale for continuous variables: Smoothed scatterplots

- In Gapminder dataset, we have 5 continuous variables:
 - CO2 Emissions
 - Food Supply
 - Income
 - Female Literacy Rate
 - Water source percent
- Plot each of these against the outcome, life expectancy

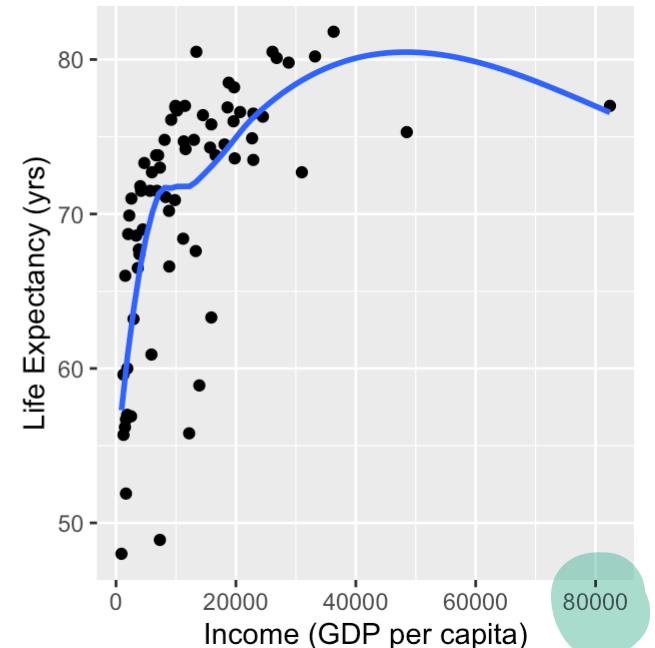
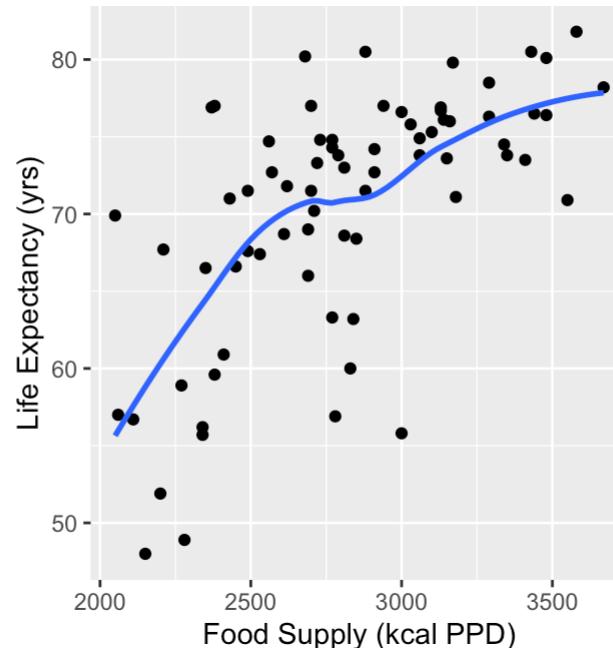
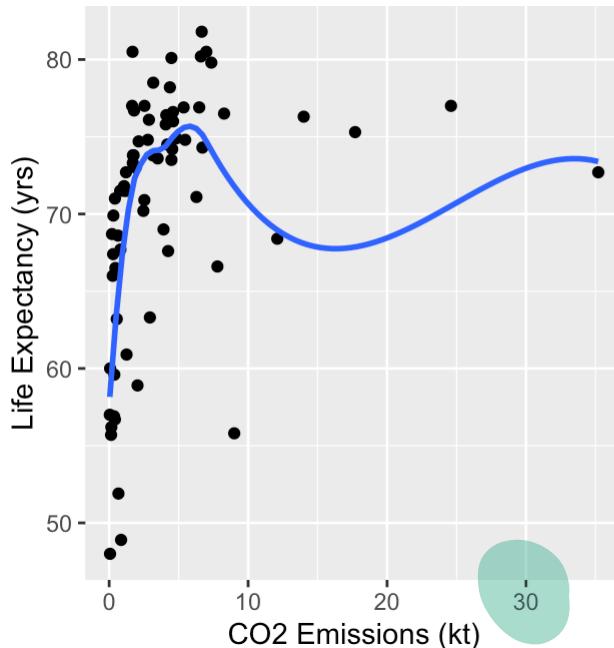
Step 4: Assess scale for continuous variables: Smoothed scatterplots

- We can quickly look at `gpairs()` to identify variables



Step 4: Assess scale for continuous variables: Smoothed scatterplots

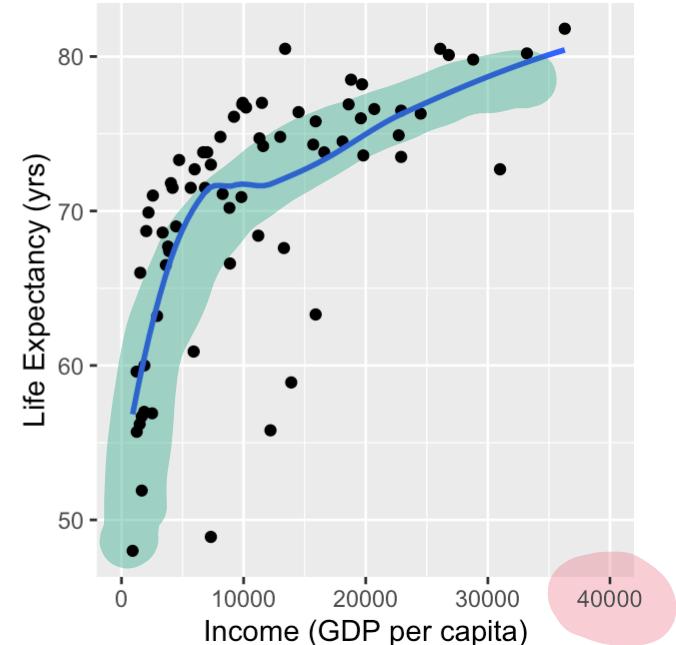
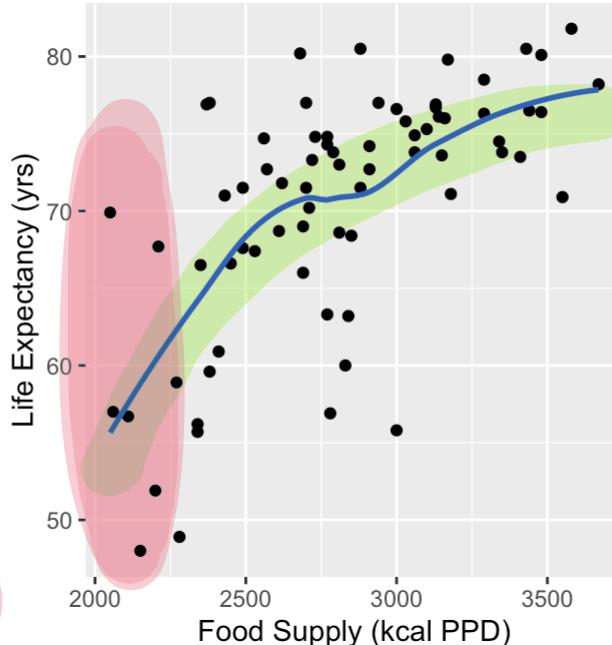
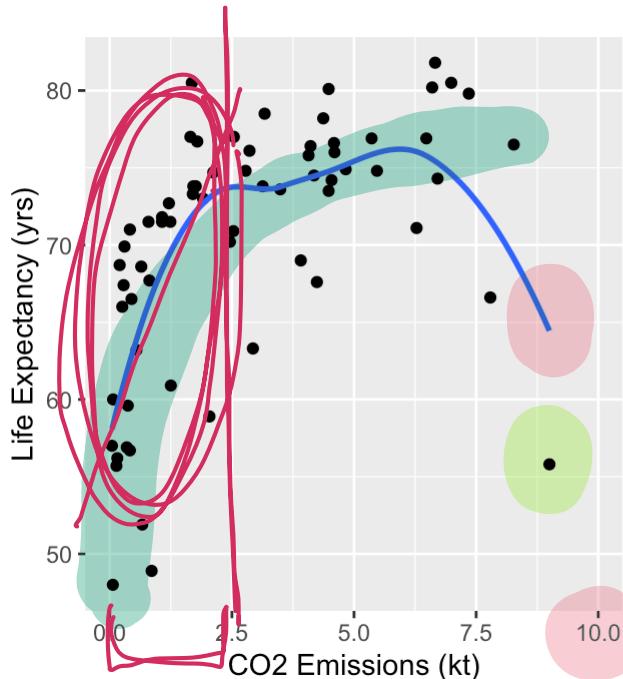
- Take a look at CO2, Food Supply, and Income



- Food Supply looks admissible
- CO2 Emissions and Income do not look very linear, but I want to zoom into the area of the plots that have most of the data

Step 4: Assess scale for continuous variables: Smoothed scatterplots

- ▶ Zoom into areas on plots with more data



- Food Supply still looks admissible
- CO2 Emissions and Income not linear: will address this!!

Step 4: Assess scale for continuous variables

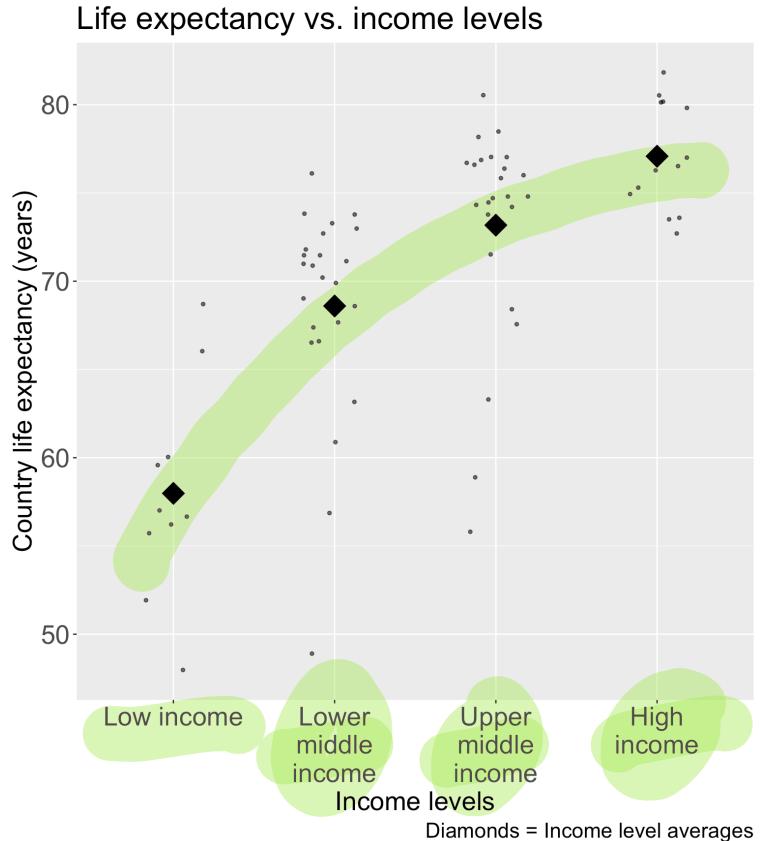
- Three methods/approaches to address the violation of linearity assumption:
 - **Approach 1:** Categorize continuous variable
 - **Approach 2:** Fractional Polynomials
 - **Approach 3:** Spline functions

Step 4: Approach 1: Categorize continuous variable

- Categorize continuous variables
 - Percentiles, quartiles, quantiles → *math driven*
 - Create indicator variables corresponding to each quartile
 - Meaningful thresholds → *expertise*
 - Example: income level groups discussed by Gapminder
- Disadvantages:
 - Takes some time to create new variables, especially with multiple continuous covariates
 - Start with quartiles, but might be more appropriate to use different splits
 - No set rules on this
- Advantage: graphical and visually helps

Step 4: Approach 1: Categorize continuous variable

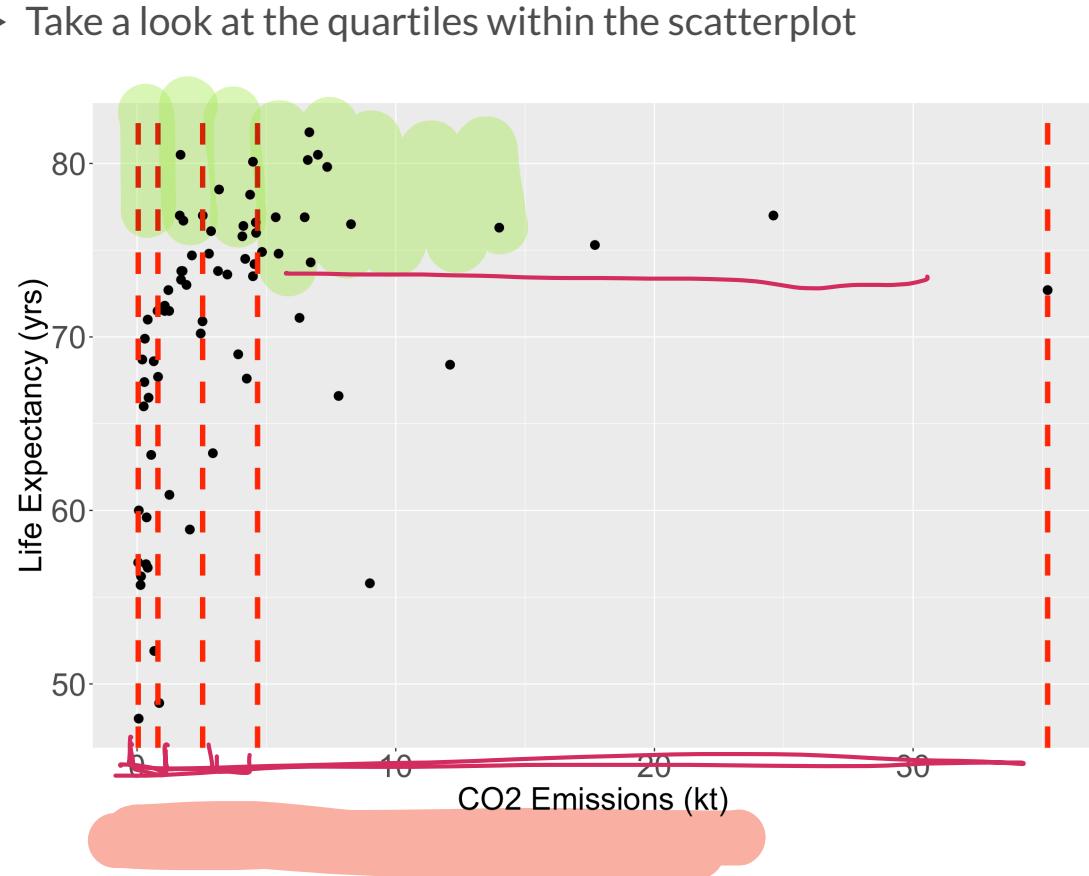
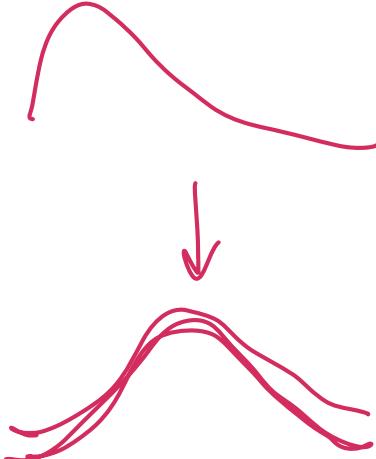
- For income, I would use **Gapminder's income level groups**
 - Discussed in Lesson 10 Categorical Covariates (slide 43)
- Experts in the field have developed these income groups
 - I think this is best solution for income (that was not meeting linearity as a continuous variable)



Step 4: Approach 1: Categorize continuous variable

- Let's still try it out with CO2 Emissions (kt) ► Take a look at the quartiles within the scatterplot
- I have plotted the quartile lines of food supply with red lines

CO₂ emissions

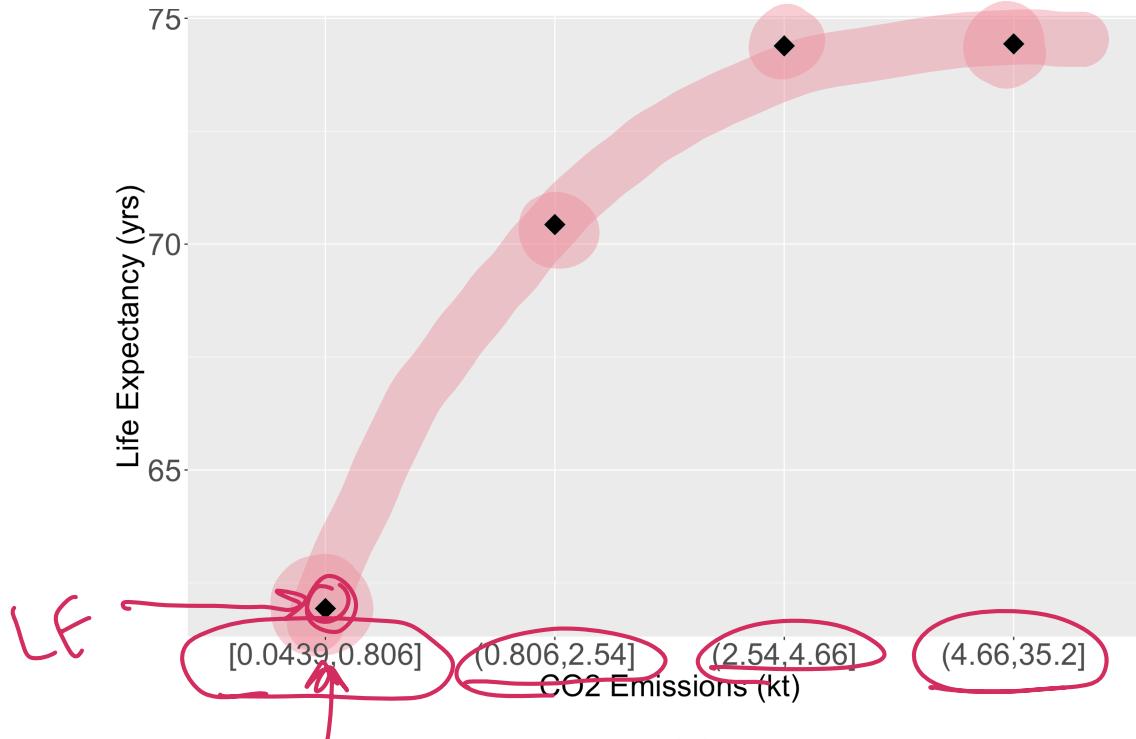


Step 4: Approach 1: Categorize continuous variable

- Let's make the quartiles for CO2 emissions:

```
1 library(dvmisc)
2 gapm2 = gapm2 %>%
3   mutate(CO2_q = quant_groups(CO2emissions, groups = 4) %>% factor())
```

- Take a look at the quartile means within the scatterplot



Step 4: Approach 1: Categorize continuous variable

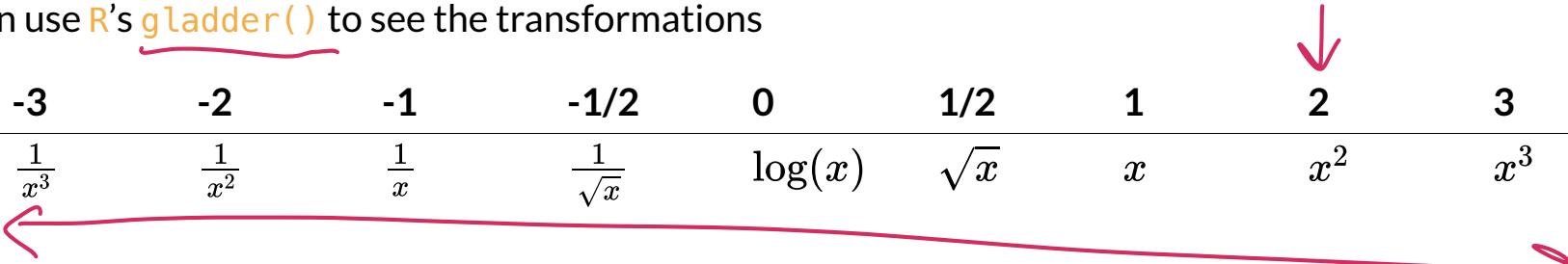
- Let's fit a new model with the two new representations for income and CO2 emissions
- Remember, this is the **main effects model** if we decide to make CO2 into quartiles

term	estimate	std.error	statistic	p.value
(Intercept)	39.877	4.889	8.157	0.000
FemaleLiteracyRate	-0.073	0.047	-1.555	0.125
CO2_q(0.806,2.54]	1.099	1.914	0.574	0.568
CO2_q(2.54,4.66]	-0.292	2.419	-0.121	0.904
CO2_q(4.66,35.2]	-0.595	2.524	-0.236	0.814
income_levels1Lower middle income	5.441	2.343	2.322	0.024
income_levels1Upper middle income	6.111	2.954	2.069	0.043
income_levels1High income	7.959	3.277	2.429	0.018
four_regionsAmericas	9.003	2.050	4.391	0.000
four_regionsAsia	5.260	1.637	3.213	0.002
four_regionsEurope	6.855	2.871	2.387	0.020
WaterSourcePrct	0.166	0.066	2.496	0.015
FoodSupplykcPPD	0.004	0.002	1.825	0.073
members_oecd_g77oecd	1.119	2.674	0.418	0.677
members_oecd_g77others	1.047	2.511	0.417	0.678

Step 4: Approach 2: Fractional Polynomials

- Main concepts and transformations presented in Lesson 7 SLR: Model Evaluation and Diagnostics (slide 33 on)
- Idea: test many transformations of a continuous covariate
 - Based on Royston and Altman, Applied Statistics, 1994
- Recall Tukey's transformation (power) ladder
 - And can use R's gladder() to see the transformations

Power p	-3	-2	-1	-1/2	0	1/2	1	2	3
	$\frac{1}{x^3}$	$\frac{1}{x^2}$	$\frac{1}{x}$	$\frac{1}{\sqrt{x}}$	$\log(x)$	\sqrt{x}	x	x^2	x^3



- We can run through each and test different models, or use the approach from Lesson 7
- There is also a package we can use!
 - **mfp package in R** contains the fp() function

Step 4: Approach 2: Fractional Polynomials

```
1 library(mfp)
2
3 fp_model_C02 = mfp(LifeExpectancyYrs ~ FemaleLiteracyRate +
4   fp(CO2emissions, df = 4) + income_levels1 + four_regions +
5   WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77,
6   data = gapm2, family = "gaussian")
7
8 fp_model_C02$fptable %>% gt(rownames_to_stub = T) %>% tab_options(table.font.size = 24)
```

Gaussian dist'n = Normal Distribution

	df.initial	select	alpha	df.final	power1	power2
four_regionsAmericas	1	1	0.05	1	1	.
four_regionsAsia	1	1	0.05	1	1	.
four_regionsEurope	1	1	0.05	1	1	.
WaterSourcePrct	1	1	0.05	1	1	.
income_levels1Lower middle income	1	1	0.05	1	1	.
income_levels1Upper middle income	1	1	0.05	1	1	.
income_levels1High income	1	1	0.05	1	1	.
FoodSupplykcPPD	1	1	0.05	1	1	.
FemaleLiteracyRate	1	1	0.05	1	1	.
CO2emissions	4	1	0.05	1	1	2 → use CO2^2 in model
members_oecd_g77oecd	1	1	0.05	1	1	.
members_oecd_g77others	1	1	0.05	1	1	

x x^2 $\log(x)$
 $x^{1/2}$

Step 4: Approach 2: Fractional Polynomials

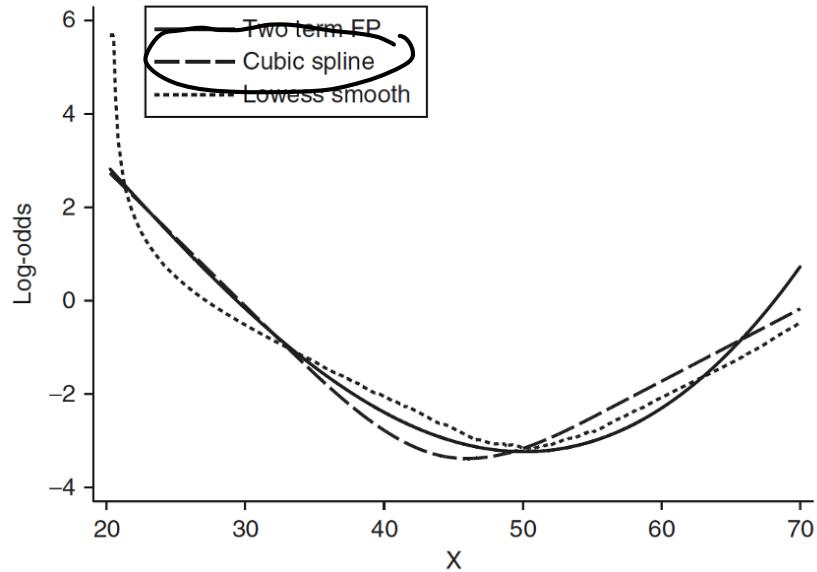
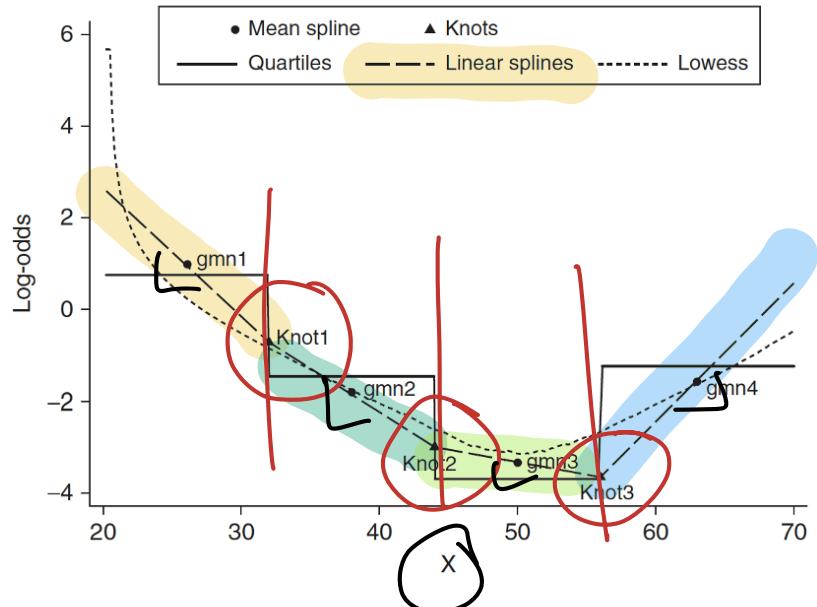
	df.initial	select	alpha	df.final	power1	power2
four_regionsAmericas	1	1	0.05	1	1	.
four_regionsAsia	1	1	0.05	1	1	.
four_regionsEurope	1	1	0.05	1	1	.
WaterSourcePrct	1	1	0.05	1	1	.
income_levels1Lower middle income	1	1	0.05	1	1	.
income_levels1Upper middle income	1	1	0.05	1	1	.
income_levels1High income	1	1	0.05	1	1	.
FoodSupplykcPPD	1	1	0.05	1	1	.
FemaleLiteracyRate	1	1	0.05	1	1	.
CO2emissions	4	1	0.05	1	1	.
members_oecd_g77oecd	1	1	0.05	1	1	.
members_oecd_g77others	1	1	0.05	1	1	.

- Conclusion from fractional polynomial is that CO2 does not need to be transformed
- A little counter-intuitive to what we saw in quartiles
- Thus, I think leaving CO2 emissions as quartiles is best!

fp() does NOT
test linearity

Step 4: Approach 3: Spline functions

- Spline function is to fit a series of smooth curves that joined at specific points (called knots)



Step 4: Approach 3: Spline functions

- Need to specify knots for spline functions
 - More knots are flexible, but requires more parameters to estimate
 - In most applications three to five knots are sufficient
- Within our class, fractional polynomials will be sufficient
- If you think this is cool, I highly suggest you look into Functional Data Analysis (FDA) or Functional Regression
 - Jeffrey Morris is a big name in that field
- In R there are a few options to incorporate splines
 - `pspline()`: [More information](#)
 - `smoothHR()`: [More information](#)

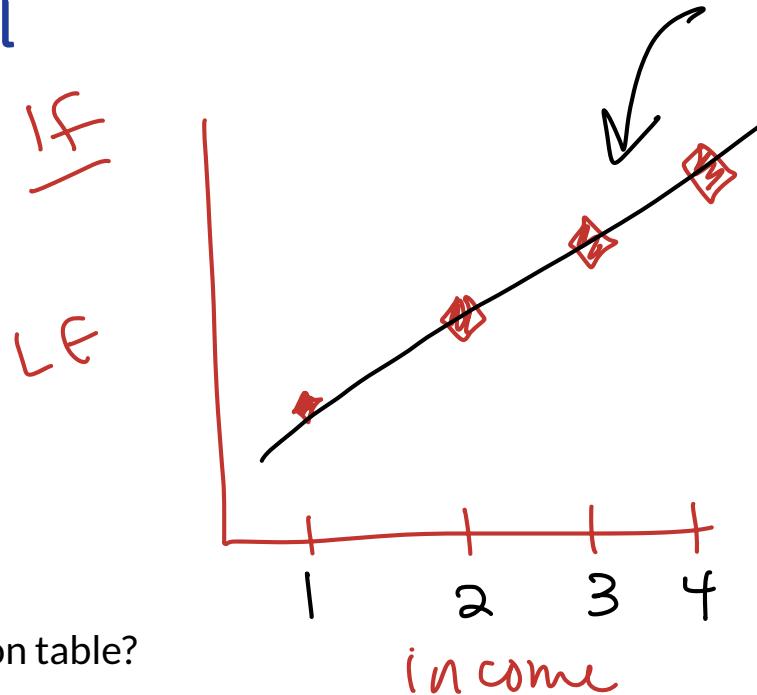
Step 4 Conclusion: main effects model

- We concluded that we will use:
 - Income levels (categorical) that Gapminder created
 - Quartiles for CO2 Emissions

Note

This is also a good step to decide if you would like to score a categorical variable ([Lesson 5](#))

- Question: Do you see any visual issues with my regression table?



Characteristic	Beta	95% CI [†]	p-value
Female literacy rate (%)	-0.07	-0.17, 0.02	0.13
CO2 emissions quartiles			
[0.0439,0.806]	quartile 1	—	
(0.806,2.54]	2	1.1	—
(2.54,4.66]	3	-0.29	0.6
(4.66,35.2]	4	-0.60	>0.9
Income levels			
Low income	—	—	
Lower middle income	5.4	0.75, 10	0.024
Upper middle income	6.1	0.20, 12	0.043
High income	8.0	1.4, 15	0.018
World region			
Africa	—	—	
Americas	9.0	4.9, 13	<0.001
Asia	5.3	2.0, 8.5	0.002
Europe	6.9	1.1, 13	0.020
Access to improved water (%)	0.17	0.03, 0.30	0.015
Food supply (kcal PPD)	0.00	0.00, 0.01	0.073
Intergovernmental group			
g77	—	—	
oecd	1.1	-4.2, 6.5	0.7
others	1.0	-4.0, 6.1	0.7

[†] CI = Confidence Interval

Learning Objectives

1. Understand the overall steps for purposeful selection as a model building strategy
2. Apply purposeful selection to a dataset using R
3. Use different approaches to assess the linear scale of continuous variables in logistic regression

Step 5: Check for interactions

- Create a list of interaction terms from variables in the “main effects model” that has clinical plausibility
- Add the interaction variables, one at a time, to the main effects model, and assess the significance using a F-test
 - May keep interaction terms with p-value < 0.10 (or 0.05)
- Keep the main effects untouched, only simplify the interaction terms
- Use methods from Step 2 (comparing model with ~~all~~ interactions to a ~~smaller~~ model with interactions) to determine which interactions to keep
 - no*
 - larger*
- The model by the end of Step 5 is called the **preliminary final model**

Step 5: Check for interactions

- We test with $\alpha = 0.10$
- Follow the F-test procedure in [Lesson 10 \(MLR: Using the F-test\)](#)
 - This means we need to follow the 7 steps of the general F-test in previous slide (taken from Lesson 10)
- Use the hypothesis tests for the specific variable combo:

Binary & continuous variable (Lesson 11, LOB 2)

Testing a single coefficient for the interaction term using F-test comparing full model to reduced model

Multi-level & continuous variables (Lesson 11, LOB 3)

Testing group of coefficients for the interaction terms using F-test comparing full to reduced model

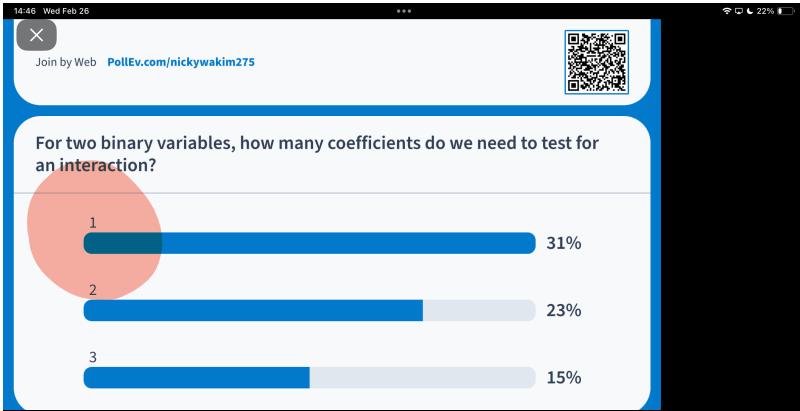
Binary & multi-level variable (Lesson 12, LOB 4)

Testing group of coefficients for the interaction terms using F-test comparing full to reduced model

Two continuous variables (Lesson 12, LOB 5)

Testing a single coefficient for the interaction term using F-test comparing full to reduced model

Poll Everywhere Questions 6-8



$$Y = \beta_0 + \underbrace{\beta_1}_\text{No} I(X_1 = \text{Yes}) + \underbrace{\beta_2}_\text{No} I(X_2 = \text{Yes}) + \underbrace{\beta_3}_\text{No} I(X_1 = \text{Yes})I(X_2 = \text{Yes})$$

(2) indicator for X_1 (#grp - 1)
(3) indicators for X_2

Step 5: Check for interactions

- Use add1() function to compare a full model (interactions with FLR) and reduced model (main effects model)

```
1 add1(main_eff_model, scope = ~ FemaleLiteracyRate * ., test = "F")
```

Single term additions

all other variables

Model:

```
LifeExpectancyYrs ~ FemaleLiteracyRate + C02_q + income_levels1 +
  four_regions + WaterSourcePrct + FoodSupplykcPPD + members_oecd_g77
```

Df	Sum of Sq	RSS	AIC	F value	Pr(>F)
----	-----------	-----	-----	---------	--------

<none>

FemaleLiteracyRate:C02_q	3	27.171	919.29	219.38	0.5320	0.6623
FemaleLiteracyRate:income_levels1	3	12.802	933.66	220.50	0.2468	0.8633
FemaleLiteracyRate:four_regions	3	95.987	850.47	213.78	2.0315	0.1203
FemaleLiteracyRate:WaterSourcePrct	1	3.040	943.42	217.25	0.1804	0.6726
FemaleLiteracyRate:FoodSupplykcPPD	1	31.063	915.40	215.07	1.9003	0.1735
FemaleLiteracyRate:members_oecd_g77	2	11.513	934.95	218.59	0.3386	0.7142

- I went through all the ANOVA tables, and found the following significant interactions:
 - None!
- **Think about it:** does that track with what we saw in our interactions lecture?

Step 6: Assess model fit

- Assess the adequacy of the model (diagnostics) and check its fit
- Methods for diagnostics will be discussed next class
 - Combination of diagnostics and model fit statistics!
 - Looked at model fit statistics in last lesson
 - Look at diagnostics in Lesson 15: MLR Diagnostics
- If the model is adequate and fits well, then it is the **Final model**

Step 6: Assess model fit

- Our **final model** contains
 - Female Literacy Rate `FLR`
 - CO2 Emissions in quartiles `C02_q`
 - Income levels in groups assigned by Gapminder `income_levels`
 - World regions `four_regions`
 - Membership of global and economic groups `members_oecd_g77`
 - OECD: Organization for Economic Co-operation and Development
 - G77: Group of 77
 - Other
 - Food Supply `FoodSupplykcPPD`
 - Clean Water Supply `WaterSupplePct`

Step 6: Assess model fit: Model fit statistics

- Way I did it in the lab instructions (and last class)

```
1 sum_fm = summary(final_model)
2 model_fit_stats = data.frame(Model = "Final model",
3                               Adjusted_R_sq = sum_fm$adj.r.squared,
4                               AIC = AIC(final_model), BIC = BIC(final_model))
5
6 model_fit_stats %>% gt() %>%
7   tab_options(table.font.size = 35) %>% fmt_number(decimals = 3)
```

Model	Adjusted_R_sq	AIC	BIC
Final model	0.743	421.804	458.230

- Another (maybe faster?) way to do it (`glance()` in `broom` package)

```
1 glance(final_model) %>% mutate(Model = "Final model") %>%
2   select(Model, adj.r.squared, AIC, BIC) %>% gt() %>%
3   tab_options(table.font.size = 35) %>% fmt_number(decimals = 3)
```

Model	adj.r.squared	AIC	BIC
Final model	0.743	421.804	458.230

Step 6: Assess model fit: Comparing model fits

- Remember the preliminary main effects model (at end of Step 3): same as final model but the continuous variables, income and CO2 emissions, were not categorized
- We can compare model fit statistics of the preliminary main effects model and the final model

```
1 fm_glance = glance(final_model) %>% mutate(Model = "Final model") %>%
2   select(Model, `Adj R-squared` = adj.r.squared, AIC, BIC)
3 pmem_glance = glance(prelim_me_model) %>%
4   mutate(Model = "Preliminary main effects model") %>%
5   select(Model, `Adj R-squared` = adj.r.squared, AIC, BIC)
6 rbind(fm_glance, pmem_glance) %>% gt() %>%
7   tab_options(table.font.size = 35) %>% fmt_number(decimals = 3)
```

Model	Adj R-squared	AIC	BIC
Final model	0.743	421.804	458.230
Preliminary main effects model	0.747	417.708	445.028

- Remember, adjusted R^2 , AIC, and BIC penalize models for more coefficients
- Preliminary main effects model: better fit statistics, but violates linearity assumption