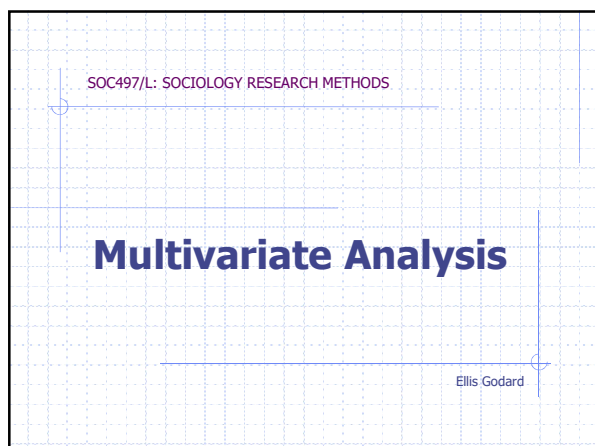


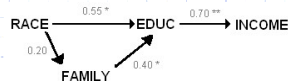
- Oral Presentations in 26 days!
- ◆ **Content**
    - Should present your research project
    - Hypo (DV, IV; others?), background, data analysis, results, concs
  - ◆ **Grading**
    - Students observing will grade each presentation
    - Five 1-5 scales: Clear? Prepared? Organize? Creative? Professional?
  - ◆ **Order**
    - First, voluntary order until no volunteers
    - Then, repeated systematic sampling (k=?) down the list
    - I'll read each name twice; if you don't come up, you get a zero
    - If all names are called b4 time's up, we're done (no class 5/11)
    - If there are still volunteers or names then, we'll continue 5/10
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- Outline for Today
- ◆ Primer on Oral Presentations (slide above)
  - ◆ Not quite Multivariate (could be 2)
    - Path Analysis & SEM
    - Time-Series Analysis
  - ◆ Beyond Bivariate (3+)
    - Factor Analysis & Cluster Analysis
    - Multiple Regression
      - With a dummy variable
      - With an interaction term
  - ◆ SPSS Demo (time permitting or in lab)
  - ◆ Lab Exercise
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## Path Analysis

- ◆ Causal model about relationships among many variables
- ◆ Graphically represents components of a cohesive model
  - See 17-3 on page 447
- ◆ Involves correlation statistic for each pair of variables
  - Between each two is a causal "link" in a chain (or path)
  - These are the *path coefficients*

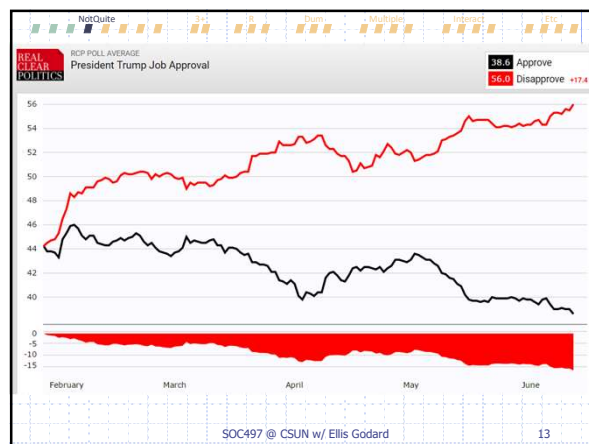


### Problems

- Does not show or tell what the causal order *should* be
- Can't confirm or falsify the order posited/theorized by researcher

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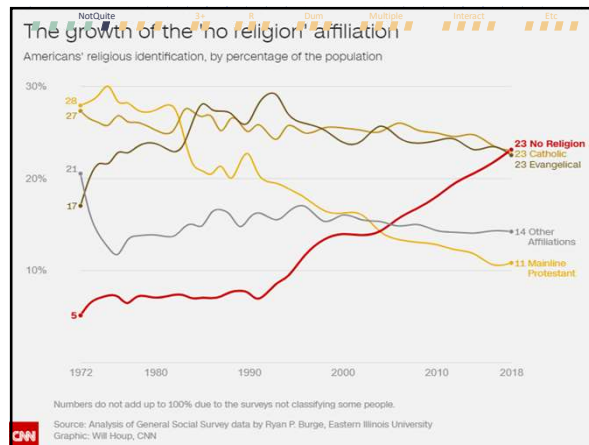


## Time Series Analysis

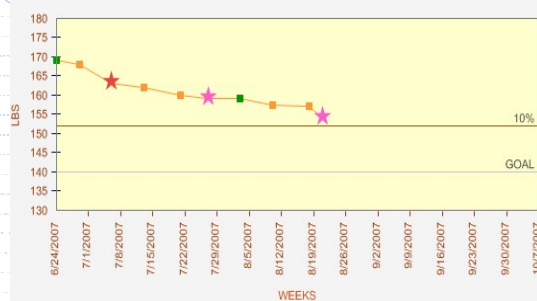
- ◆ Represent changes in one or more variables over time.
  - Population and crime rates change over time for a city
  - Time "just" becomes one of the variables
- ◆ Time as a control variable
  - See multiple regression
- ◆ Time-lagged regression analysis
  - e.g. relate larceny rate to *previous* year's unemployment rate
  - Compare across years to see if that relation changes over time

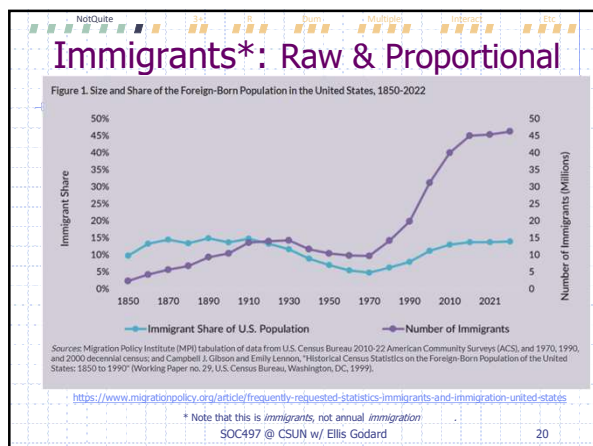
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## Example: Weight Loss Chart

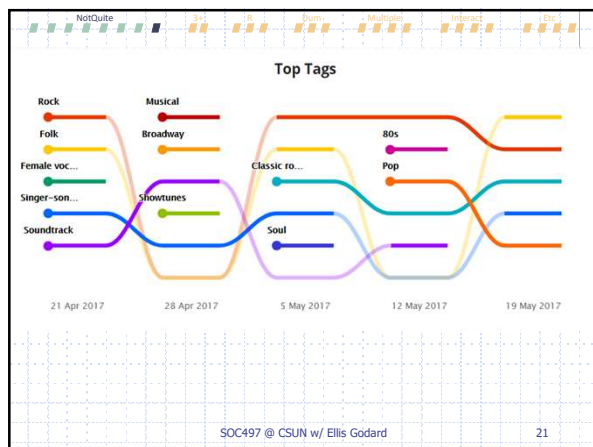




## Q2: Which addresses the correlations for separate relationships in an overall model?

- A. Dummy variables 0%
- B. Factor Analysis 33%
- C. Interaction Terms 3%
- D. Path Analysis 65%
- E. Time Series Analysis 0%

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## Linear Regression

- ◆ General formula to describe assoc. between 2 variables
  - $Y = f(X)$
  - $Y = a + bx$  (not  $mx + b$ )
  - $INCOME = 3.4 + 863 * EDUC$

- ◆ Can be used to predict values of Y, given values of X
- ◆ There is always an implicit error term ( $y = a + bx + i$ )

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## Factor Analysis

- ◆ Used to discover patterns among several variables
  - Like simultaneous correlations
    - Complex algebra; *not* by hand
  - But about grouping variables (like indices), not cause/effects
  - Generates eigen values suggest which variables "go together"
- ◆ Problems:
  - Generates factors w/o substantive meaning
    - Combining variables is a *measurement* decision
    - Factor "loadings" assess statistical relationship among variables, rather than correlative dimensions of the same concept
  - Facilitates *ad hoc* & *post hoc* analyses
    - Grouping variables ought to be for theoretical reasons
    - Grouping based on 1 dataset risks patterns due to sampling bias
  - Result aren't falsifiable
    - *Something will always hold together* as loaded factors

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## Benefits of that "Assumption"

- ◆ Describes the relationship between 2 variables
- ◆ Inferential values: Allows us to predict...
  - ...the *average* value of the DV for each value of the IV
  - ...the *avg increase* in DV, for each *increase of 1* in IV

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
1 (Constant)	223.190		1.393	.160
1 Index of online media use	<b>5.102</b>	.386	2.291	<b>.025</b>

a. Dependent Variable: weight

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.201 <sup>a</sup>	.041	.040	79.830

a. Predictors: (Constant), Index of online media use

- ...how much of the variance in the DV is explained by variance in the IV
- Can write equation:
  - **Weight = 223.190 + (5.102\*OLUSE)**
  - Note p values

Note that equations include variable names!



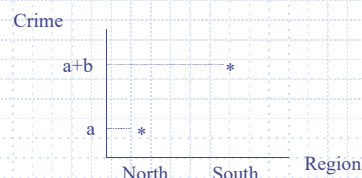
### Q3: A regression equation...

- A. summarizes evidence against line of best fit  
0%
- B. always includes an interaction term  
3%
- C. always includes an implicit error term  
97%
- D. connects as many points as possible  
0%
- E. Always involves two nominal variables  
0%

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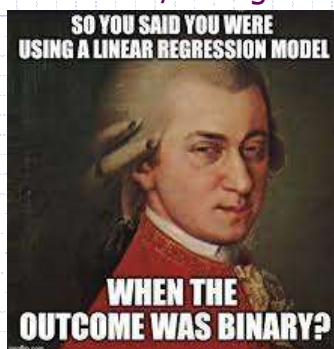
### Regional Differences in Crime



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### Don't use SLR w/ Categorical DVs



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### Multiple Regression

- ◆ More than one independent variable (X)
- ◆ A different slope (b) for each one, e.g.
  - $INCOME = 2.4 + 535*EDUC - 158*KIDS$
- ◆ Each IV has its own coefficient (e.g. 535, 158)
  - Each slope is the *average predicted* change in Y for each increase of 1 in *that* X
- ◆ ONE equation for ALL of the variables
  - NOT a separate equation for each variable
  - No limit to the number or type of variables
  - Can plug in values of IV, to predict value of DV

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### Dummy Variables

- ◆ Consider a model that uses Region to predict crime rates
  - Region has 5 nominal categories
  - Slope doesn't make sense if include all 5; assumes settled order
- ◆ Instead, create a new variable for each region
  - SOUTH has two values, 0 and 1
  - 1 means the state is in the South; 0 means it isn't
- ◆ Using a dummy as the IV
  - The equation using only that one IV would be:  
 $Crime = a + b(South)$
  - The crime rate in the South is:  
 $Crime = a + b(1) = a + b$
  - The crime rate in the North is:  
 $Crime = a + b(0) = a$

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### Multiple Regression w/ 1 Dummy: Region, Urbanization and Crime

- ◆ We hypothesize that crime is a function of urbanity and southernness – that is, that it will be higher in cities and in the south.
- ◆ Assuming the relationship is linear, the regression equation would be:  
 $Crime = a + b_1(Urban) + b_2(South)$

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## Multiple Regression Equations

- ◆ For the non-south cases, one part of the equation “falls out”, leaving 2 equations:

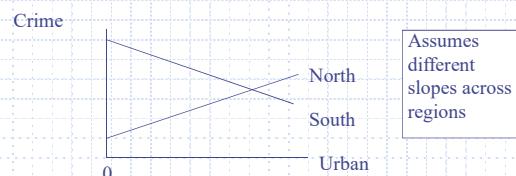
$$\begin{aligned} \text{Crime}_{\text{South}} &= a + b_1(\text{Urban}) + b_2(1) \\ &= a + b_1(\text{Urban}) + b_2 \end{aligned}$$

$$\begin{aligned} \text{Crime}_{\text{North}} &= a + b_1(\text{Urban}) + b_2(0) \\ &= a + b_1(\text{Urban}) \end{aligned}$$

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## Plot with Interaction Term Included: Region, Urbanization and Crime

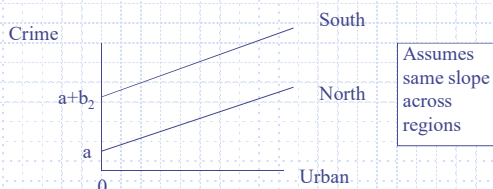


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## Multiple Regression Plots

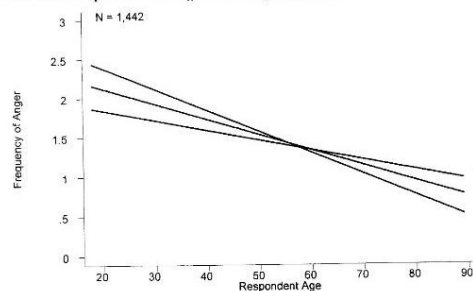
- ◆ Since we have 2 equations, we have 2 lines:



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## The Relationship between Age and Anger at Different Levels of Education



Note: Lines correspond to equation 2 of Table 1 and reflect predicted anger frequency scores for white men. Intercepts will vary slightly with other combinations of sex and race. Lines 1, 2, and 3 reflect predictions for individuals with 17, 13, and 10 years of education, respectively. These education values are the 90th, 50th, and 10th percentiles.

Scott Schieman, "Socioeconomic Status and the Frequency of Anger Across the Life Course", In *Sociological Perspectives* (Journal of the PSA), Vol 46, No. 2 (Summer 2003), pp. 207-222.

## Regression w/ Interaction Term: Region, Urbanization and Crime

$$\text{Crime} = f(\text{Urban}, \text{Region}, \text{Urban} * \text{Region})$$

Create “interaction” term btwn Urban and Region:  
COMPUTE=SOUTH\*URBAN

$$\text{Crime} = a + b_1(\text{Urban}) + b_2(\text{South}) + b_3(\text{Urban} * \text{South})$$

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## Q4: Which is most like an index?

- A. Dummy variable 66%
- B. Interaction term 13%
- C. Path coefficient 16%
- D. Pinky finger 5%
- E. Do you really want a 5th option to struggle with? No, you don't. So, don't pick this one 0%

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