Methods of Applied Statistics I

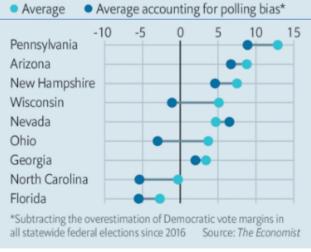
STA2101H F LEC9101

Week 5

October 12 2022

If you believe they're biased...

US Senate races, Democratic vote margin in pre-election polls, percentage points September 14th 2022



The Economist



Today

- 1. Upcoming events
- 2. Recap
- 3. Steps in analysis; types of studies
- 4. In the News
- 5. HW 4 3rd hour
- 6. Sections for Project
 - a description of the scientific problem of interest
 - how (and why) the data being analyzed was collected
 - preliminary description of the data (plots and tables)
 - models and analysis
 - summary for a statistician of the analysis and conclusions
 - non-technical summary for a non-statistician of the analysis and conclusions

Upcoming

- October 13 3.30-4.30 : DoSS Seminar Room 9014 (Hydro Building)
- Brenda Betancourt, U Chicago
- Microclustering for record linkage applications

Brenda<u>Betancourt</u> NORC – University of Chicago



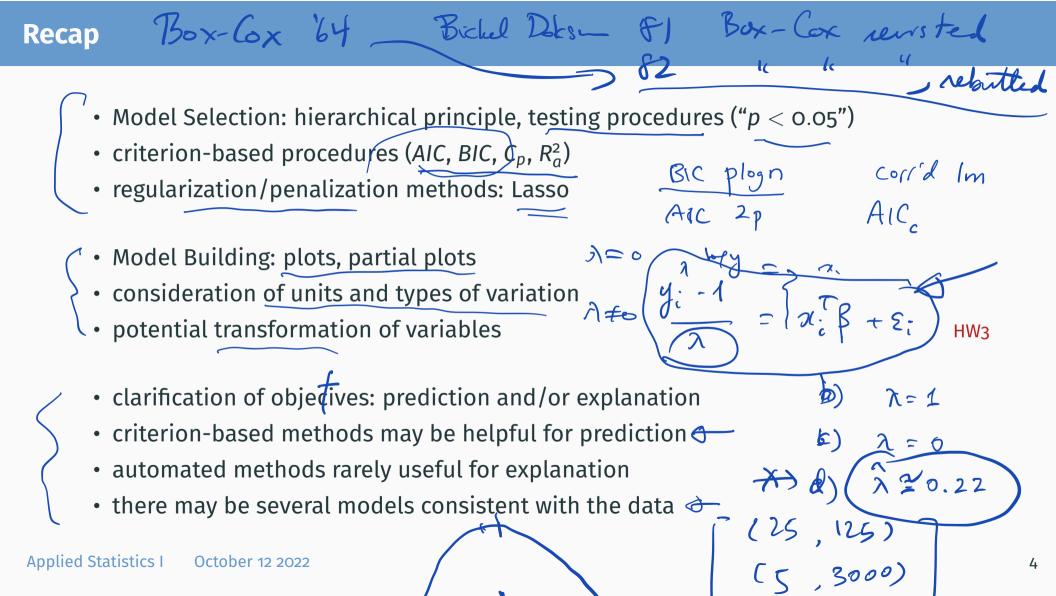
Brenda is currently a Senior Statistician at NORC at the University of Chicago. Before joining NORC, she was an Assistant Professor in the Department of Statistics at the University of Florida. She obtained her PhD in Statistics at the University of California, Santa Cruz and was a postdoctoral fellow at Duke University working on Bayesian models and algorithms for record linkage and Network analysis.

Microclustering for record linkage applications

Upcoming

- October 15 12.00-1.00 Toronto Data Workshop; Room BL520, Bissell Building and online link
- April Wang, U Michigan

"Reimagining Tools for Collaborative Data Science"



- common objectives
- to avoid systematic error, that is distortion in the conclusions arising from sources that do not cancel out in the long run

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L (10,700)

CD, **Ch**.2

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Design of Studies

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Gras

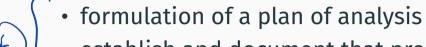
• to ensure that the scale of effort is appropriate

CD, Ch.2

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- in most situations synthesis of information from different investigations is needed

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- in most situations synthesis of information from different investigations is needed
- but even there the quality of individual studies remains important
- examples include overviews (such as the Cochrane reviews)
- in some areas new investigations can be set up and completed relatively quickly; design of individual studies may then be less important



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- planned analysis may be technically inappropriate
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Latter will require confirmatory studies

Unit of study and analysis

- smallest subdivision of experimental material that may be assigned to a treatment context: Expt
- Example: RCT unit may be a patient, or a patient-month (in crossover trial)
- Example: public health intervention unit is often a community/school/...
- split plot experiments have two classes of units of study and analysis
- in investigations that are not randomized, it may be helpful to consider what the primary unit of analysis would have been, had a randomized experiment been feasible $E(\epsilon_y) = 0$ but $\hat{\epsilon} \neq \epsilon$

$$E\left(\hat{z}\hat{y}\right) = 0 \quad \underbrace{\mathcal{E}}_{\mathbf{y}} \quad \underbrace{\mathcal{L}}_{\mathbf{y}} \quad \text{not} \quad \mathcal{L}_{\mathbf{y}} \quad E\left(\hat{z}y\right)$$

$$\underset{\text{ancosrid}}{\text{ancosrid}} \quad \underbrace{\mathcal{L}}_{\mathbf{y}} \quad \underbrace{\mathcal{L}}_{\mathbf{z}} \quad \underbrace{\mathcal$$

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i=1,.-, n

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 the unit of analysis may not be the unit of interpretation – ecological bias systematic difference between impact of x at different levels of aggregation

- CD: Illustration "For country- or region-based mortality data, countries of regions respectively may reasonably constitute the units of analysis with which to assess the relationship of the data to dietary and other features
- "Yet the objective is interpretation at an individual person level
- "The situation may be eased if supplementary data on explanatory variables are available at the individual level, because this may clarify the connection of between-unit and within-unit variation"

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- feelings of well-being are associated with socio-economic status
- the strength of the association is larger in developed nations than in developing nations
- conventional explanation: in nations with a high level of economic development perhaps higher SES carries some intrinsic value
- this paper: in nations with a high level of religiosity, the strength of the association between SES and well-being is weaker
- religiosity could attenuate the link between well being and SES Economist, Sep 25 2021

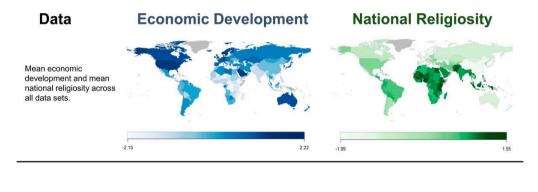


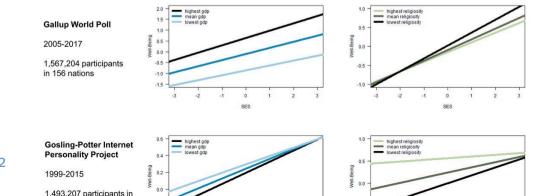


6DP



Distribution of national economic development, national religiosity, and estimated means of the cross-level interactions (model 3).





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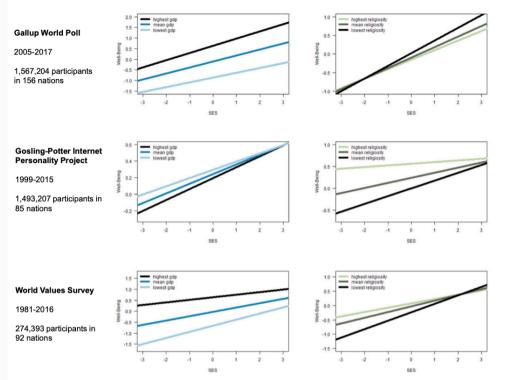


Fig. 2. Distribution of national economic development, national religiosity, and estimated means of the cross-level interactions (model 3). The top row depicts mean national economic development and mean national religiosity worldwide (z-standardized and averaged across data sets). Lighter colors represent lower values, darker colors higher values. The three bottom rows depict estimated marginal means of the cross-level interactions when both national noderators were included in the model (i.e., model 3). Depicted are the moderating effects of national economic development and national religiosity on the association between SES and well-being in all three data sets.

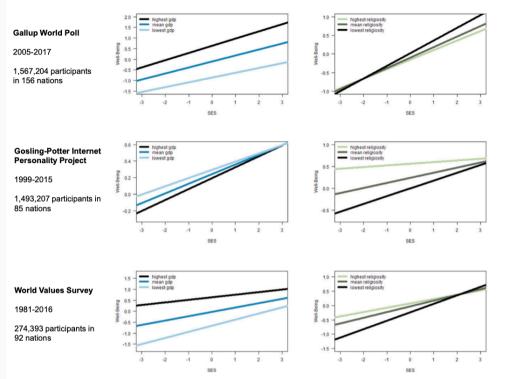
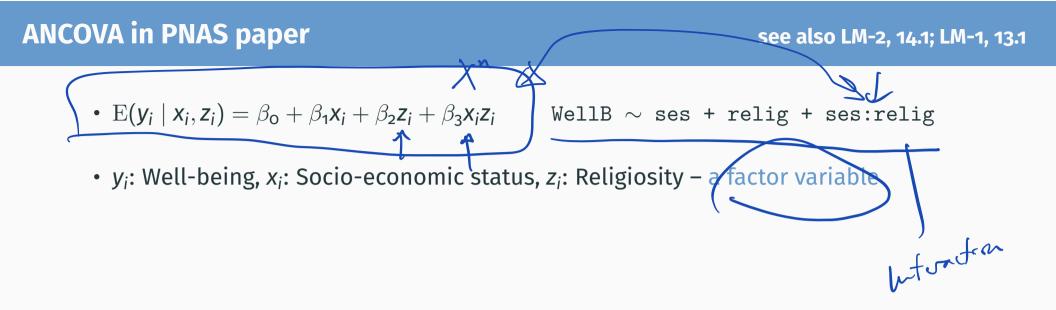


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ANCOVA in PNAS paper

see also LM-2, 14.1; LM-1, 13.1

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• $E(y_i \mid x_i, z_i) = \beta_0 + \beta_1 x_i + \beta_2 z_{ij} + \beta_3 x_i z_{ij}$ WellB ~ ses + relig + ses:relig • y_i: Well-being, x_i: Socio-economic status, z_i: Religiosity – a factor variable SES religned religning *z_i* = ("low", "medium", "high") model.matrix $E(y_i \mid x_i, z_i = "low") = \beta_0 + \beta_1 x_i$ $E(y_i \mid x_i, z_i = "med") = \beta_0 + \beta_2 + (\beta_1 + \beta_4) x_i$ $E(y_i \mid x_i, z_i = "med") = \beta_0 + \beta_3 + (\beta_1 + \beta_5) x_i$ $E(y_i \mid x_i, z_i = "hi") = \beta_0 + \beta_3 + (\beta_1 + \beta_5) x_i$ 0 • as usual, the paper's a bit more complicated some data collected on people, and some on countries (multi-level model) • "Following standard practice, we averaged person-level religiosity within each nation " • there's another covariate **F**GDP "Following a standard economic method, we log-transformed the GDP data" **Applied Statistics I** October 12 2022 regression la TI confo & 1 factor

Factor variables: modelling

- a factor variable is treated as categorical
- a non-factor variable is treated as continuous
- it depends on the application which is preferred

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- a non-factor variable is treated as continuous
- it depends on the application which is preferred
 - a linear model with one factor and one continuous variable might be written as, for example:

$$\mathbf{y}_{ij} = \mu + \alpha_j \left(+ \beta \mathbf{x}_{ij} \right) + \epsilon_{ij}, \quad \mathbf{j} = 1, \dots, \mathbf{J}; \quad \mathbf{i} = 1, \dots, \mathbf{m}$$

• linear in x, but arbitrary changes in $\mathbb{E}(y)$ by category (here indexed by j)

J-level factor

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FLM-2 §14.4; FLM-1 §13.3

Rac

$$E \mathbf{y}_{ij} = \mu + \alpha_j + \beta \mathbf{x}_{ij} + \epsilon_{ij}, \quad \mathbf{j} = 1, \dots, \mathbf{J}; \quad \mathbf{i} = 1, \dots, \mathbf{M}$$

- linear in x, but arbitrary changes in $\mathbb{E}(y)$ by category (here indexed by j)
- R doesn't distinguish this at the modelling phase:

 $lm(response \sim variable1 + variable2, data = ...)$

but uses metadata in the data frame to accommodate factors

()

• is.factor(variable) and newvar <- as.factor(oldvar) are helpful

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Supplementary material

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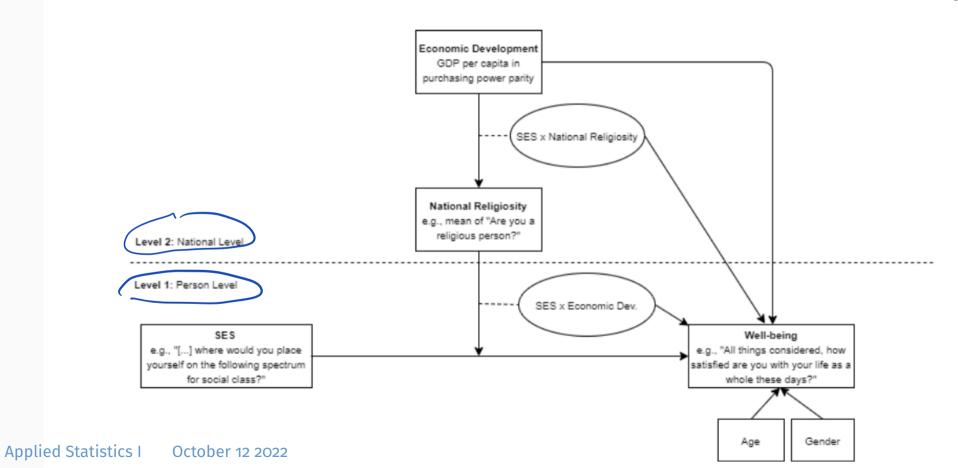


Figure S1. Mixed Effects Mediated Moderation Model (model 4). Statistical model to calculate the portion of the cross-level interaction

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Observational studies

SM 9.1, LM-2 5.4, LM-1 3.7

"correlation is not causation"

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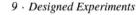
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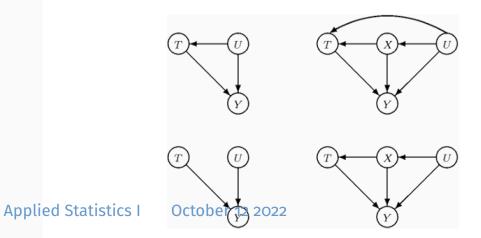


Figure 9.1 Directed acyclic graphs showing consequences of randomization. An arrow from T to Y indicates dependence of Y on T. and so forth. In general both response Y and treatment T may depend on properties U of units (upper left). Randomization (lower left) makes treatments and units independent, so any observed dependence of Y on T cannot be ascribed to joint dependence on U. The upper right graph shows the general dependence of Y, T, and covariates X on U.

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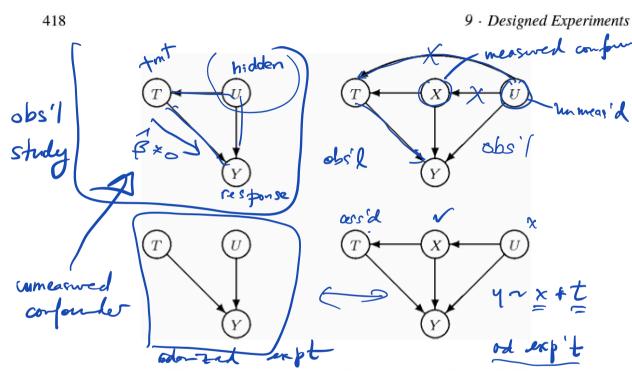


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the control group. The response is to be the blood pressure of an individual measured a fixed time after the drug has first been administered. We calculate the average changes for the treated and control groups, \overline{y}_1 and \overline{y}_0 , observe that $\overline{y}_1 - \overline{y}_0$ is significantly less than zero, and declare that the drug plays an effect in reducing blood pressure. Is this headline news? No!

A key difficulty is that the procedure does not avoid biased allocation of treatments to units. For example, if the control group mostly consisted of those patients with

Support for causation

LM-2 5.7

Bradford - Hill criteria

- strength of the association
- · consistency of the association across many exp'ts

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- specificity of the proposed causal factor
- potential cause occurs before its effect (temporality)
- dose-response relationship
- a subject-matter theory exists
- "natural experiments" e.g. minimum wage

• secondary analysis of data collected for another purpose

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- estimation of some feature of a defined population

could in principle be found exactly

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 - at several time points for different individuals
 - at different time points for the same individual

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- study of a relationship between features, where individuals may be examined
 - at a single time point
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- census
- meta-analysis: statistical assessment of a collection of studies on the same topic

Modelling numbers/proportions of events

•
$$y_i \sim Bin(6, p_i), \quad i = 1, ..., 23$$

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Modelling numbers/proportions of events

- $y_i \sim Bin(6, p_i), \quad i = 1, ..., 23$
- in general: *n_i* trials, *y_i* successes, probability of success *p_i*
- for regression: associated covariate vector x_i, e.g. temperature
- SM uses m_i and r_i instead of n_i and y_i
- each y_i could in principle be the sum of n_i independent Bernoulli trials
- each of the n_i trials having the same probability p_i
- with the same covariate vector x_i

FELM 'covariate classes', p.26

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Challenger data: Faraway

```
> library(faraway); data(orings)
> logitmod <- glm(cbind(damage,6-damage) ~ temp, family = binomial, data = orings)</pre>
> summary(logitmod)
Call:
glm(formula = cbind(damage, 6 - damage) ~ temp, family = binomial,
    data = orings)
. . .
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 11.66299 3.29626 3.538 0.000403 ***
temp -0.21623 0.05318 -4.066 4.78e-05 ***
```

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 38.898 on 22 degrees of freedom Residual deviance: 16.912 on 21 degrees of freedom

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Challenger data: Davison

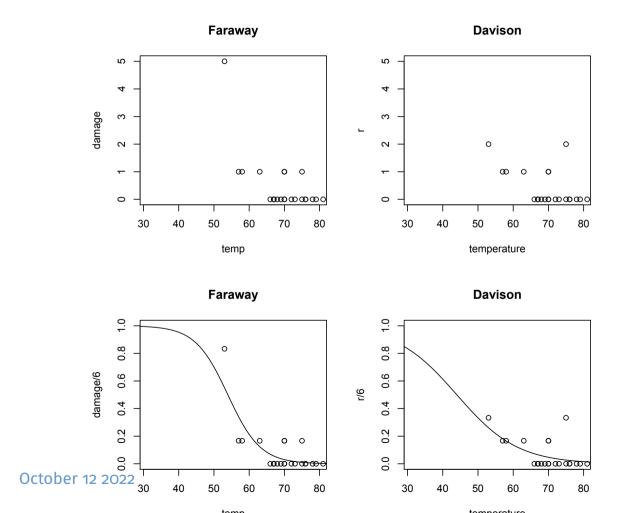
```
> library(SMPracticals) # this is for datasets in
                          #Statistical Models by Davison
> data(shuttle) # same example, different name
> shuttle2 <- data.frame(as.matrix(shuttle)) # this is a kludge to avoid
                                   #an error with head(shuttle)
> head(shuttle2)
 m r temperature pressure
1 6 0
               66
                        50
2 6 1
               70
                        50
3 6 0
               69
                        50
4 6 0
               68
                        50
560
               67
                        50
6 6 0
               72
                        50
> par(mfrow=c(2,2)) # puts 4 plots on a page
```

> with(orings,plot(temp,damage,main="Faraway",xlim=c(31,80)))

```
> with(shuttle,plot(temperature,r,main="Davison",xlim=c(31,80),
```

+ ylim=c(0,5)))

Challenger data fits



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