Statistical challenges in the study of aging and dementia

Karen Bandeen-Roche Professor of Biostatistics & Medicine

December 11, 2007

### Some challenges for statistics...

- Change is key
- Measurement is tough
  - Errors
  - Multidimensional constructs
  - Indirect; maybe differential



- Sicker people refuse, *drop out*, skip, die
- Aging is **complex**

#### ...leads to statistical challenges

- Longitudinal data analysis
- *Measurement* modeling
  - Errors-in-variables
  - Data reduction techniques, e.g., principal components
  - Latent variable modeling
- Missing data, competing risks analysis
- Mathematical *modeling*

# Objective

# For you to walk away with specific, useful information on at least one of the challenges:

#### ...leads to statistical challenges

- Longitudinal data analysis
- *Measurement* modeling
  - Errors-in-variables
  - Data reduction techniques, e.g., principal components
  - Latent variable modeling
- Missing data, competing risks analysis
- Mathematical *modeling*

#### Why longitudinal data analysis (LDA)?

- Top ten reasons
- 10. Because it will make me look so cool
  - 9. Because a grant reviewer will call my application "unsophisticated" if not

(I'm only creative enough to come up with two of these....)

## Why LDA?

- Top four reasons
  - 4. To inform policy

- Changes in disability prevalence over time

3. To study natural histories

- Functional trajectories and their etiologies

- 2. To make prognoses, incorporating history — Cognitive status transitions
- To progress from "association" toward "cause"

   Intervention A or risk adoption B changes outcomes

#### What I Hope You'll Get Out of This

- The basic longitudinal modeling methods
- How one implements those methods
  - Key models
  - Software
- Heads up on the primary challenges

#### An Example Emotional vitality and mobility

- Study: Women's Health & Aging (n=1002; Guralnik et al., 1995)
- Question: Does emotional vitality affect mobility trajectory?
  - Emotional vitality (X: 1 if vital; 0 ow)
    - High mastery, being happy, few depressive/anxious symptoms

Penninx et al., 2000

- Mobility (Y)
  - Usual walking speed (max 2 trials)
  - Indicator of severe walking difficulty (1 if yes; 0 ow)
- Time (T)
  - Study rounds 0-6

The basic longitudinal methods *Diggle, Heagerty, Liang & Zeger, 2001* 

- Top four reasons
  - 4. To inform policy

- Population average (marginal models; GEE)

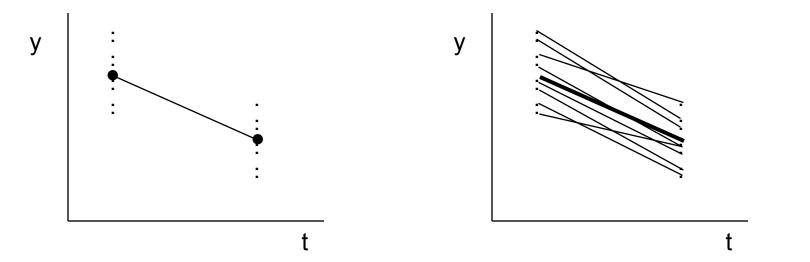
3. To study natural histories

– Subject-specific (random effects; growth curves)

- 2. To make prognoses, incorporating history
  - Transitions (autoregressive & Markov models)
- To progress from "association" toward "cause"

   Time-varying covariates (with complexities)

#### Population average v. Subject-Specific



- PA: Compare populations over time
  - (Fixed) time effect = slope of the averages
- SS: Compare women to selves over time
  - (Fixed) time effect = average of the slopes
- Subtle point: These are equal
  - with continuous outcomes Y (linear regression); NOT otherwise
  - provided that within-person correlation is explicitly accounted for

### Population-average models

- Keywords
  - Marginal models
  - GEE (Generalized Estimating Equations)

Liang & Zeger, 1986

- Panel analysis
- Sound bites
  - Focus usually on averages (their trajectories)
  - Serial correlation often a "nuisance"
  - "Robust"

#### Population-average models Description of average trajectories

• Model—time-invariant covariates:

$$Y_{i1} = \beta_0 + \beta_1 x_i + \beta_2 t_{i1} + \beta_3 x_i t_{i1} + e_{i1}$$

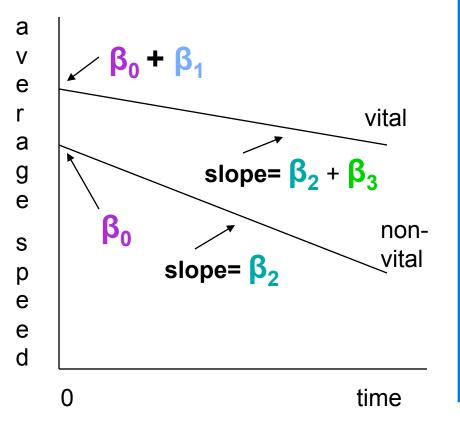
$$Y_{ij} = \beta_0 + \beta_1 x_i + \beta_2 t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$$

$$Y_{i7} = \beta_0 + \beta_1 x_i + \beta_2 t_{i7} + \beta_3 x_i t_{i7} + e_{i7}$$

$$Key_f points_n$$
average walk\_spaced  
of non-vital persons  
- "ANCOVA" model
$$main effects for "treatment"$$

• Note contrast viz "change scores": more powerful

#### Population-average models Pictures



- Data displays
  - Side-by-side <u>box</u>
    <u>plots</u> (by time,
    "treatment")
  - <u>Connect-the-means</u> plots (over time, by treatment)
  - Y versus t <u>smoothed</u> <u>scatterplot</u>, per x

 $Y_{ij} = \beta_0 + \beta_1 x_i + \beta_2 t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$ 

#### Population-average models Treatment of serial correlation

 $Y_{i1} = \beta_0 + \beta_1 x_i + \beta_2 t_{i1} + \beta_3 x_i t_{i1} + e_{i1}$ 

 $Y_{ij} = \beta_0 + \beta_1 x_i + \beta_2 t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$ 

$$Y_{i7} = \beta_0 + \dot{\beta_1} x_i + \beta_2 t_{i7} + \beta_3 x_i t_{i7} + e_{i7}$$

- Key points error: amount that speed of woman "i" Errors are corrected atom within persons
  - Most software rayout timedse the correlation "structure"
    - "Exchangeable" all measures equally strongly correlated
    - "Autoregressive," "banded" measures closer in time more strongly correlated
    - "Unstructured" as it sounds (here: 7 choose 2 = 21 ρs)
    - "Independence" all correlations assumed = 0

#### Population-average models: Fitting

- Software
  - <u>SAS</u>: GENMOD (GEE); MIXED, repeated (MLE)
  - <u>SPSS</u>: Advanced model package
  - <u>Stata</u>: xtgee (GEE); xtreg (MLE)
- GEE versus MLE (maximum likelihood est.)
  - Both: accurate coefficient estimates whether or not correlation structure choice is correct
  - -GEE: standard errors also accurate, regardless
  - MLE: More valid handling of missing data

### Subject-specific models

- Keywords
  - Mixed effects, growth curves, multi-level
  - Mixed model; hierarchical (linear) model GEE Laird & Ware, 1982; Raudenbush & Bryk, 1986
  - Random coefficient model
- Sound bites
  - Focus usually on individual trajectories
  - "Heterogeneity": variability of trajectories
  - Assumptions are made, and may matter

Subject-specific models Average & individual trajectories

Model—time-invariant covariates:

$$Y_{i1} = \beta_0 + b_{0i} + \beta_1 x_i + \beta_2 t_{i1} + b_{2i} t_{i1} + \beta_3 x_i t_{i1} + e_{i1}$$

$$Y_{ij} = \beta_0 + b_{0i} + \beta_1 x_i + \dot{\beta}_2 t_{ij} + b_{2i} t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$$

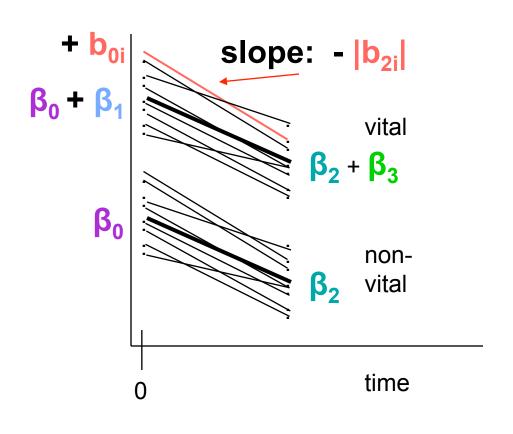
$$Y_{i7} = \beta_0 + b_{0i} + \beta_1 x_i + \dot{\beta}_2 t_{i7} + b_{2i} t_{ij} + \beta_3 x_i t_{i7} + e_{i7}$$

- Key points:
  - The additional coefficients are range differs from average

amount speed

- Modeling assumes a distribution: usually normal
  - Distribution variable to haracterizes "heterogeneity"
  - Heterogeneity results in within-person correlation
- One may define correlation structure for e<sub>ii</sub>s too

#### Subject-specific models Pictures



b<sub>0i</sub> = random intercept
 b<sub>2i</sub> = random slope
 (could define more)

 heterogeneity (
 spread in intercepts, slopes

• Sentinel data display: spaghetti plot (Ferrucci et al., 1996)

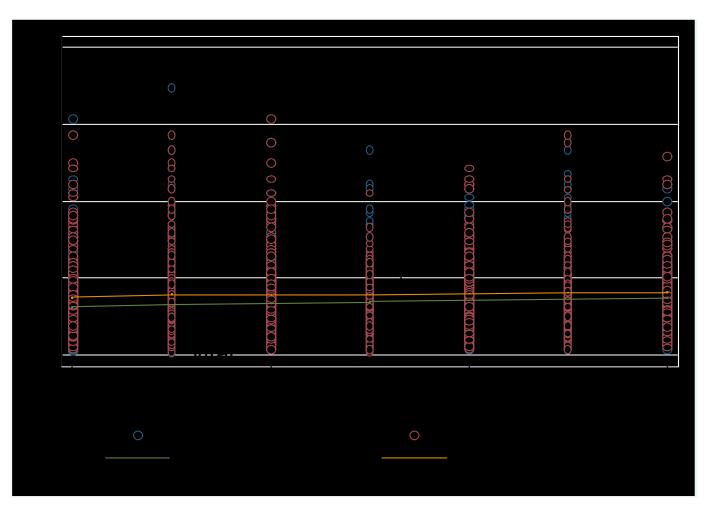
 $Y_{ij} = \beta_0 + b_{0i} + \beta_1 x_i + \beta_2 t_{ij} + b_{2i} t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$ 

### Subject-specific models: Fitting

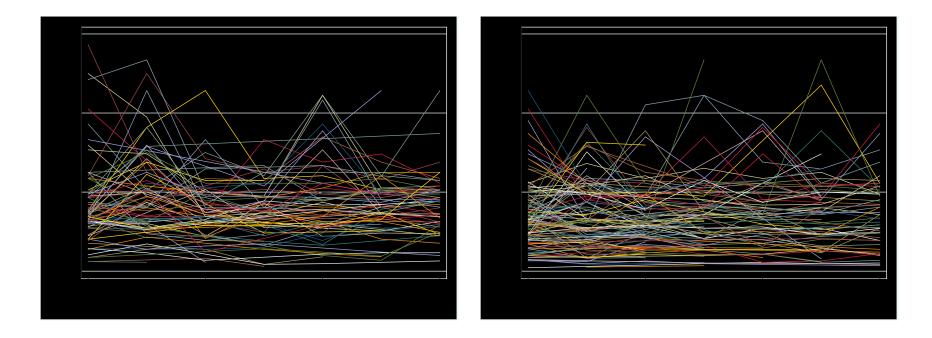
- Software
  - <u>SAS</u>: MIXED, random; GLIMMIX (macro);
     NLMIXED
  - <u>SPSS</u>: Advanced model package
  - <u>Stata</u>: xt... sequence
  - Other: HLM, MLWIN, Splus, R, winbugs
- Sister formulation: latent growth curve



#### Usual Walking Speed in WHAS Panel Plot



#### Usual Walking Speed in WHAS Spaghetti Plots



Emotionally vital

Emotionally non-vital

### Usual Walking Speed in WHAS Does vitality affect walking speed?

Parameter	ML: Independent	GEE: exchangeable	ML: unstructured	ML: Random b <sub>0</sub> & b <sub>1</sub>
Intercept	.58 (.010)	.63 (.035)	.57 (.012)	.58 (.012)
Vitality	.10 (.017)	.075 (.050)	.10 (.020)	.10 (.020)
Time	.0026 (.003)	031 (.012)	012 (.0022)	012 (.002)
Vit*time	0015 (.005)	.017 (.018)	.0068 (.0035)	.0062 (.0034)
Main effects model: Intercept, vitality results very similar to above				
Time	.0020 (.0024		0091 (.002)	0094 (.002)
	wrong	002)		

#### Usual Walking Speed in WHAS Heterogeneity

- Residual SD, variance: 0.167, .0280
  - Represents variability of a woman's speeds "about" her own regression line
- Intercept SD, variance: 0.276, .0762
  - "Test-retest" estimate = .076/(.076+.028)=.73
- Slope SD, variance: 0.031, .00094
  - 95% of slopes estimated within +/-.06 of ~-.01
- Intercept, slope covariance: .0020

- Correlation=.23: better trajectories for better starters

Unstructured correlations: .6 - >.99

– Highest late in the study

#### Vitality & Walking Speed in WHAS Summary

- Beneficial association with emotional vitality
  - Begin better by ~.1; 95% CI ~ [.06,.14]
  - Moderate evidence: Decline rate ~ halved
- Remarkable stability evidenced
  - Modest average decline
  - Heterogeneity: moderate  $\downarrow$  to modest  $\uparrow$
  - Stability increased with duration in study
- To advance toward "causation": much needed
  - Control for confounders
  - Change on change

Population average v. Subject-Specific How to choose?

- Science
- Advantages of subject-specific models
  - Characterization of heterogeneity–estimates
  - May well embody mechanisms
- Advantages of marginal models
  - More robust
    - Standard errors valid if correlation model wrong (GEE)
    - Fixed effect estimates distribution-insensitive

- Computationally faster, more transportable (GEE)

• An MLE advantage: Missing data treatment

## Why LDA?

- Top four reasons
  - 4. To inform public policy

- Changes in disability prevalence over time

3. To study natural histories

- Functional trajectories and their etiologies

- 2. To make prognoses, incorporating history — Cognitive status transitions
- 1. To progress from "association" toward "cause"

- Intervention A or risk adoption B changes outcomes

### **Transition Models**

- <u>Basic idea</u>: control model for current outcome on all past outcomes
  - "Autoregressive" errors
  - Modify marginal model to include past "Y"s as predictors in model for Y<sub>it</sub>
- <u>Often assumed</u>: current outcome only depends on the one most immediately past
  - Model for  $Y_{it}$  includes  $Y_{it-1}$  but no other Ys
  - "First order Markov"

Beckett et al.,1996

#### Some important LDA Challenges

- Feedback, endogeneity
  - Decline in speed may erode emotional vitality... or, the vital may try harder at the measured walk test
- Dropout, missing data

   Key distinction: ignorable, non-ignorable
- Nonlinear & clustered trajectories

   Thresholds, changepoints, trajectory classes

### Take home points

- If you're out to save Millions at a Time<sup>©</sup>
  - Population average (marginal) model
    - Choice 1: GEE (corr-robust) vs. MLE (missing-robust)
    - Choice 2: Association structure to fit?
  - Mean trajectory estimates not sensitive
- If one at a time, or seeking to target
  - Subject-specific (random effect) model
  - Benefit if model correct: heterogeneity characterization, missing-robust, MLE: precise
- Prognosis based on history: transitions

#### An Introduction to Latent Variable Models

#### LATENT VARIABLES: TRUTH, LIES, AND EVERYTHING BETWEEN

Karen Bandeen-Roche Department of Biostatistics Johns Hopkins University

**December 11, 2007** 

### Objectives For you to leave here knowing...

- What is a latent variable?
- What are some common latent variable models?
- What is the role of assumptions in latent variable models?
- Why should I consider using—or decide against using—latent variable models?

#### ALATENT@

Present or potential but not evident or active: latent talent.
 Pathology. In a dormant or hidden stage: a latent inf ection.
 Biology. Undeveloped but capable of normal growth under the proper conditions: a latent bud.

4. Psychology. Present and accessible in the unconscious mind but not consciously expressed.

The American Heritage7 Dictionary of the English Language, Fourth Edition, 2000

Accurate a second secon

Merriam-Webster's Dictionary of Law, 1996

#### ALATENT@

#### A. concepts in their purest f orm.....>nobserved=or >nmeasured=. hypothetical@

Bollen KA, Structural Equations with Latent Variables p. 11, 1989

#### A. in principle or practice, cannot be observed@

Bartholomew DJ, The Statistical Approach to Social Measurement, p. 12, 1996

AUnderlying: not directly measurable. Existing in hidden f orm but usually capable of being measured indirectly by observables

Bandeen-Roche K, Synthesis, 2006

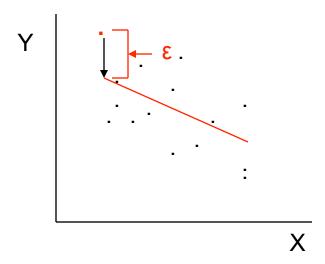
#### **ALATENT VARIABLES@**

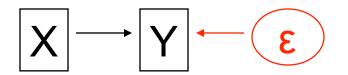
**Ordinary linear regression model:** 

 $Y_{i} = outcome \ (measured)$   $\underline{X}_{i} = covariate \ vector \ (measured)$  $\varepsilon_{i} = residual \ (unobserved)$ 

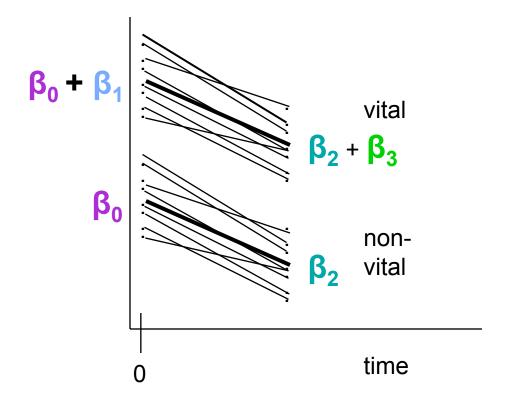
 $\mathbf{Y}_{\mathbf{i}} = \mathbf{\underline{X}}_{\mathbf{i}}^{\mathrm{T}} \mathbf{\underline{\beta}} + \mathbf{\underline{\epsilon}}_{\mathbf{i}}$ 

## Ordinary Linear Regression Residual as Latent Variable



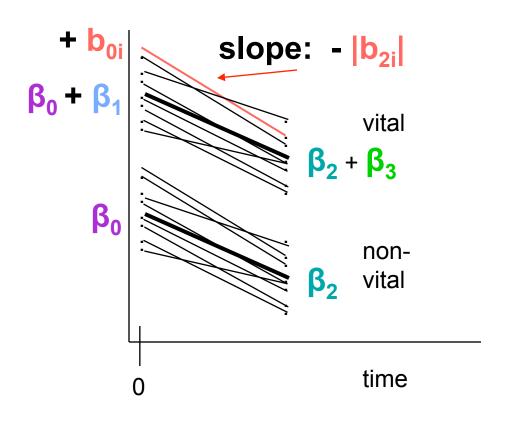


## Mixed effect / Multi-level models Random effects as Latent Variables



 $Y_{ij} = \beta_0 + \beta_1 x_i + \beta_2 t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$ 

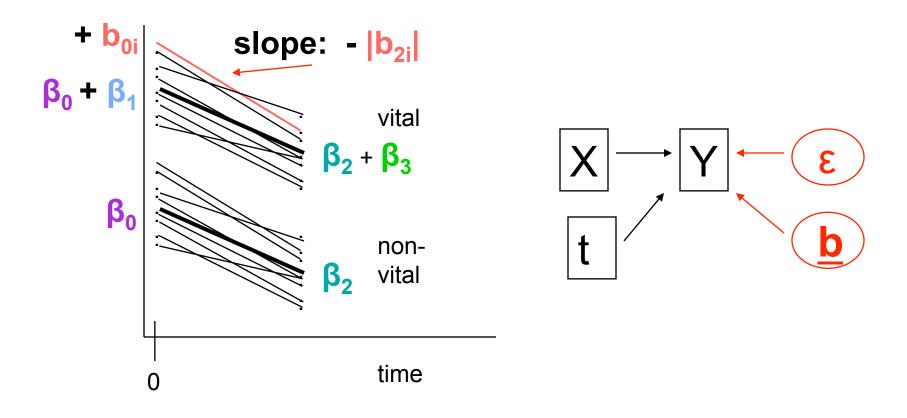
## Mixed effect / Multi-level models Random effects as Latent Variables



•	b <sub>0i</sub> = random intercept
	b <sub>2i</sub> = random slope
	(could define more)
•	Population
	heterogeneity
	captured by
	spread in
	intercepts, slopes

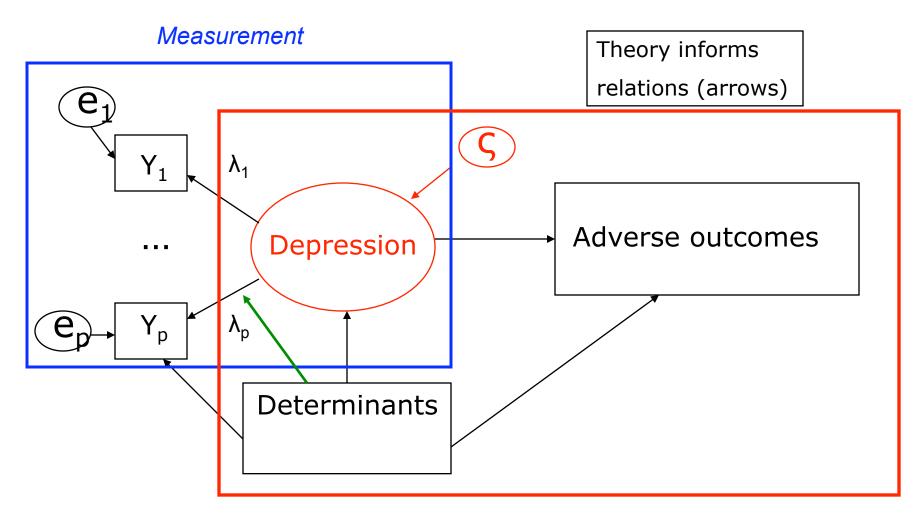
 $Y_{ij} = \beta_0 + b_{0i} + \beta_1 x_i + \beta_2 t_{ij} + b_{2i} t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$ 

Mixed effect / Multi-level models Random effects as Latent Variables



$$Y_{ij} = \beta_0 + b_{0i} + \beta_1 x_i + \beta_2 t_{ij} + b_{2i} t_{ij} + \beta_3 x_i t_{ij} + e_{ij}$$

## Depression Latent Variable Illustration



Structural

# Why do people use latent variable models?

- The complexity of my problem demands it
- NIH wants me to be sophisticated
- Reveal underlying truth (e.g. "discover" latent types)
- Operationalize and test theory
- Sensitivity analyses
- Acknowledge, study issues with measurement; correct attenuation; etc.

## Well-used latent variable models

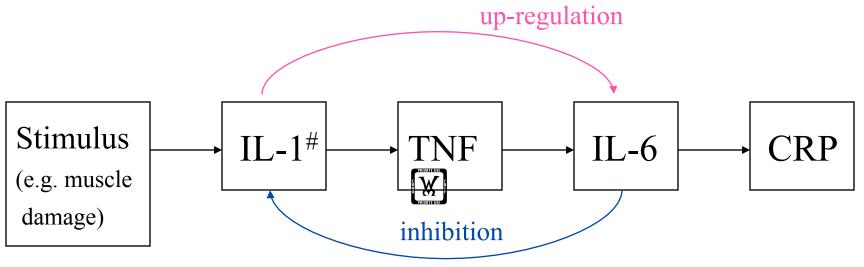
Latent variable	Observed variable scale		
scale	Continuous	Discrete	
Continuous	Factor analysis LISREL	Discrete FA IRT (item response)	
Discrete	Latent profile Growth mixture	Latent class analysis, regression	

General software: MPlus, Latent Gold, WinBugs (Bayesian), NLMIXED (SAS)

LISREL software: LISREL, AMOS, CALIS (SAS)

## Example: Theory Infusion

- Inflammation: central in cellular repair
- Hypothesis: dysregulation=key in accel. aging
  - Muscle wasting (Ferrucci et al., JAGS 50:1947-54; Cappola et al, J Clin Endocrinol Metab 88:2019-25)
  - Receptor inhibition: erythropoetin production / anemia (Ershler, JAGS 51:S18-21)

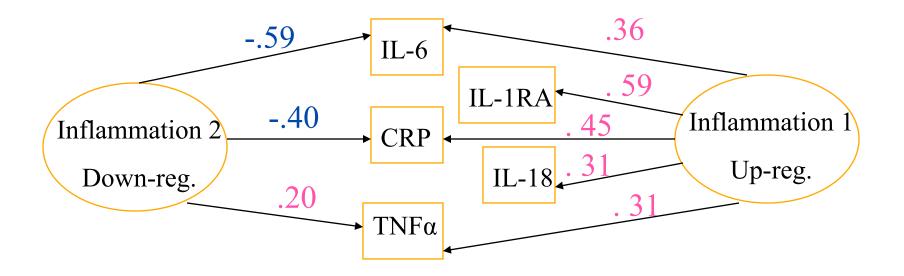


# Difficult to measure. IL-1RA = proxy

## Theory infusion

InCHIANTI data (Ferrucci et al., JAGS, 48:1618-25)

- LV method: factor analysis model
  - two independent underlying variables
  - down-regulation IL-1RA path=0
  - conditional independence



#### **Application: Post-traumatic Stress Disorder Ascertainment**

#### ! PTSD

C Follows a qualifying traumatic event

> This study: <u>personal assault</u>, <u>other personal inj ury/traum</u>a <u>trauma to loved one</u>, <u>sudden death of loved one</u> = A@along with gender

C Criterion endorsement of symptoms related to the event  $\Box$  diagnosis > Binary report on 17 symptoms = AY@

A recent study (Chilcoat & Breslau, Arch Gen Psych, 1998)
 C Telephone interview in metropolitan Detroit
 C n=1827 with a qualifying event

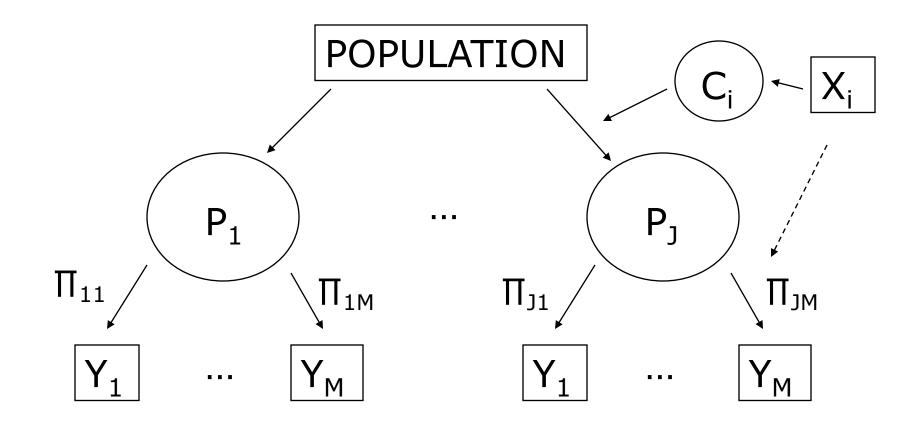
C Analytic issues

> Nosology

> Does diagnosis differ by trauma type or gender?

> Are f emale assault victims particularly at risk?

### Analysis of underlying subpopulations Latent class analysis / regression



19-Goodman, 1974; 27-McCutcheon, 1987

## Analysis of underlying subpopulations Method: Latent class analysis/ regression

Seeks homogeneous subpopulations

 Assumption: reporting heterogeneity unrelated to measured or unmeasured characteristics

 - conditional independence, non differential measurement by covariates of responses within latent groups : partially determine features

- Features that characterize latent groups
  - Prevalence in overall population
  - Proportion reporting each symptom
  - Number of them

#### **PTSD Study: Descriptive Statistics**

Gender	Trauma Type: percentage distribution				n
	Personal Assault	Other Inj ury	Trauma to loved one	Sudden death	
Male	14.2	37.7	26.9	21.3	964
Female	14.3	26.3	32.2	27.2	863
Total	14.2	32.3	29.4	24.1	1827

PTSD symptom criteria met: 11.8% (n=215)

- C By gender:8.3% of men, 15.6% of womenC By trauma:assault (26.9%), sudden death (14.8%),otherinj ury (8.1%), trauma to loved one (6.0%)
- C <u>Interactions</u>: female x assault  $(\square)$ , female x other  $(\square)$
- C <u>Criterion issue</u>? 60% reported symptoms short of diagnosis

#### **Latent Class Model for PTSD: 9 items**

SYMPTOM	SYMPTOM (prevalence)	SYMPTOM PROBABILITY (π)		
CLASS		Class 1 - NO PTSD	Class 2 - SOME SYMPTOMS	Class 3 - PTSD
RE-	Recurrent thoughts (.49)	.20	.74	.96
EXPERIENCE	Distress to event cues (.42)	.12	.68	.88
	Reactivity to cues (.31)	.05	.51	.77
AVOIDANCE/	Avoid related thoughts (.28)	.08	.37	.75
NUMBING	Avoid activities (.24)	.05	.34	.66
	Detachment (.15)	.01	.14	.64
INCREASED	Difficulty sleeping (.19)	.02	.18	.78
AROUSAL	Irritability (.21)	.02	.22	.83
	Difficulty concentrating (.25)	.03	.30	.89
MEAN PREVAL	ENCE-BASELINE	.52	.33	.14

[Omitted: nightmares, flashback; amnesia, linterest, laffect, short future; hypervigilance, startle]

#### **PTSD: DIAGNOSIS, LCR MEASUREMENT MODEL**

! <u>Method</u>: Regress item responses on covariates Acontrolling@for class C For simplicity: non-assaultive traumas merged into Acther trauma@

Variable	Odds Ratio or Interaction Ratio (CI)	By-item Odds Ratio MODEL 2
Female	1.07 (0.93,1.22)	1.07 (0.93,1.22)
Trauma =other than assault (recur.)	3.19 (1.89,5.40)	3.19 (1.89,5.40)
Cue distress x other trauma	0.18 (0.09,0.38)	0.58 (0.36,0.92)
Cue reactivity x other trauma	0.14 (0.07,0.28)	0.44 (0.27,0.72)
Avoid thoughts x other trauma	0.21 (0.11,0.41)	0.68 (0.44,1.05)
Avoid activities x other trauma	0.11 (0.05,0.22)	0.35 (0.21,0.58)
Detachment x other trauma	0.27 (0.13,0.58)	0.88 (0.51,1.49)
Difficulty sleep x other trauma	0.43 (0.21,0.90)	1.37 (0.78,2.42)
Irritability x other trauma	0.28 (0.13,0.61)	0.91 (0.52,1.59)
Concentration x other trauma	0.73 (0.36,1.47)	2.33 (1.35,4.03)

#### Summary PTSD Analysis

- ! The analysis hypothesizes that PTSD is
  - C a syndrome comprising <u>unaffected</u>, <u>subclinically affected</u>, and <u>diseased</u> subpopulations of those suffering traumas
  - C reported homogeneously within subpopulations
- ! The hypotheses are consistent with current diagnostic criteria
- ! <u>Gender x type interactions</u>: are strongly indicated
  - C Female assault victims at particular risk
  - ${\sf C}$  ... given the subpopulations defined by the model

#### Summary PTSD Analysis

! Symptoms appeared differentially sensitive to different traumas

<u>Within classes</u>: those who had a non-assaultive trauma were

C less prone to report <u>distress to cues</u>, <u>reactivity to cues</u>, <u>avoiding</u> <u>thoughts</u>, & <u>avoiding activities</u>

C more prone to report <u>recurrent thoughts</u> & <u>difficulty concentrating</u>

! <u>Concern</u>: Current criteria may better detect psychiatric sequelae to assault than to traumas other than assault

## Objectives

For you to leave here knowing...

- What is a latent variable?
- What are some common latent variable models?
- What is the role of assumptions in latent variable models?
- Why should I consider using—or decide against using—latent variable models?

#### DISCUSSION

#### **The Debate over Latent Variable Models**

- ! In favor: they
  - C acknowledge measurement problems: errors, differential reporting
  - C summarize multiple measures parsimoniously
  - C operationalize **theory**
  - C describe population heterogeneity

#### ! Against: their

C modeling assumptions may determine scientific conclusions

#### C interpretation may be ambiguous

- > Nature of latent variables (*existence*)?
- > Unique (*identif iability*?
- > Comparable fit of very different models (*estimability*)?
- > Seeing is believing (*can the model be checked*)?

# Some closing thoughts

- Useful information?
  - Enrichment for reading the literature
  - A sense of what's possible
  - Priming for thinking about study design
- Something to build on
  - Courses
  - Seminars
  - Mentoring