Welcome to instats

The Session Will Begin Shortly

(At the top of the hour, Eastern USA time)

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START

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Nonlinear Time Series Analysis, Part II: Modeling and Phenomenology

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Seminar Outline

- Day 1
  - Session 1 – Overview of Phenomenology
  - **Session 2 – Dynamical Systems Analysis**
- Day 2
  - Session 3 – Sparse Identification of Nonlinear Dynamics
  - Session 4 – Dynamic Mode Decomposition
- Day 3
  - Session 5 – Hidden Markov Models
  - Session 6 – Machine Learning Approaches
- Day 4
  - Session 7 – Putting it All Together: Lorenz
  - Session 8 – Putting it All Together: Infectious Diseases

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Dynamical Systems Analysis

- Dynamical Systems Analysis
- Conceptual Introduction to Differential Equations
  - Theorizing with derivatives
- Writing Equations
  - Converting to MLM
  - Estimating the model
  - Interpreting the model
- Latent classes

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Differential Equations

- Conceptually
  - Colloquially: Level, velocity (rate of change of level), acceleration (rate of change of velocity), jerk, snap, crackle, pop
  - Derivatives: 0^{th}, 1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th}, 6^{th}
  - Equations: Various order derivatives in same equation
- Solutions
  1. Method of “judicious guessing”
     - Linear: guess exponential functions
  2. Ugh

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Differential Equations: Theorizing

- *Impedance* components:
  - *Mass*
  - *Stiffness*
  - *Resistance (power)*
- Combinations
  - {Mass, stiffness} yields oscillations
  - {Mass, stiffness, resistance} yields decaying oscillations
  - {Increasing stiffness} yields nonlinear oscillations
  - Etc.

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Writing Model Equations

- Cause and effect
  - Theorize what should be involved
  - Takes some practice
- Endogenous v. Exogenous
  - Exogenous events often randomly timed relative to endogenous dynamics

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Example: Post-trauma

- Mastery and Despair
  - Coping self efficacy
    - Not level (alone)
    - Velocity is important
- Impact of post-traumatic growth on distress
  - Level not significant!
  - Acceleration significant

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Example: Resistance v. Recovery

- Montpetit et al. (2010)
  - Stress resistance
  - Stress recovery
- Needs derivatives

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Multilevel Modeling

- Data Nesting
  - Within measure, across times
  - Within individual, across measures
  - Within group, across individuals
- Recall:
  - Parameter estimates ok
  - Inference not ok

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Multilevel Modeling

- Converting to MLM
  - Rationale: measurements over time nested within individuals
  - Sadly: Level and level
    - CAPTIAL “Level” for multilevel Levels
    - lowercase “level” for 0^{th} derivatives

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Interpretation

- Interpretation is hard in MLM
  - Interpretation with derivatives in MLM is harder
- Group estimates?
- Individual estimates?
  - Within group
- Inference?

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Example: Montpetit et al. (2010)

- Dynamic
  - Negative Affect (N_{it})
  - Negative Stress (S_{it})
- Traits
  - Dispositional resilience (DR_i)
  - Family Support (FM_i)
  - Friend Support (FR_i)

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Example: Montpetit et al. (2010)

$$\ddot{N}_{it} = \eta_{1i} N_{it} + \zeta_{2i} \dot{N}_{it} + \gamma_{3i} \ddot{S}_{it} + e_{it} \qquad \text{(Level 1)}$$

- N_{it} is Negative Affect for person *i* at time *t*
- η_{1i} is related to the frequency of oscillation
- ζ_{2i} is related to the damping
- γ_{3i} is the coupling between accelerating Stress and accelerating Negative Affect
- S_{it} is the stress level.

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Example: Montpetit et al. (2010)

$$\ddot{N}_{it} = \eta_{1i} N_{it} + \zeta_{2i} \dot{N}_{it} + \gamma_{3i} \ddot{S}_{it} + e_{it} \qquad \text{(Level 1)}$$
$$\eta_{1i} = \beta_{10} + \beta_{11} DR_i + \beta_{12} FR_i + \beta_{13} FM_i + u_i \qquad \text{(Level 2)}$$
$$\zeta_{2i} = \beta_{20} + \beta_{21} DR_i + \beta_{22} FR_i + \beta_{23} FM_i + u_i \qquad \text{(Level 2)}$$
$$\gamma_{3i} = \beta_{30} + \beta_{31} DR_i + \beta_{32} FR_i + \beta_{33} FM_i + u_i \qquad \text{(Level 2)}$$

- DR_i is dispositional resilience
- FR_i is friend support
- FM_i is family support

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Example: Montpetit et al. (2010)

- Now for the stress equations

$$\ddot{S}_{it} = \eta_{4i}S_{it} + \zeta_{5i}\dot{S}_{it} + \gamma_{6i}\ddot{N}_{it} + e_{it} \qquad \text{(Level 1)}$$
$$\eta_{4i} = \beta_{40} + \beta_{41}DR_i + \beta_{42}FR_i + \beta_{43}FM_i + w_i \qquad \text{(Level 2)}$$
$$\zeta_{5i} = \beta_{50} + \beta_{51}DR_i + \beta_{52}FR_i + \beta_{53}FM_i + w_i \qquad \text{(Level 2)}$$
$$\gamma_{6i} = \beta_{60} + \beta_{61}DR_i + \beta_{62}FR_i + \beta_{63}FM_i + w_i \qquad \text{(Level 2)}$$

- Everything defined in parallel to the previous equations

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Example: Montpetit et al. (2010)

- Run in R

- Look at their results/interpretation
  - This is NOT a MLM course, though…

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Latent Classes

- Clustering
  - Individual time series may be similar
  - Latent classes
- Appraches
  - Growth mixture modeling (GMM / LGCM)
  - K-Means Longitudinal (KML)
  - Growth Curve K-Means (GCKM)

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K-Means Clustering

- Cluster N objects into K groups
- Clustering Process
  - Pick K mean locations
  - Iteration Step
    - Assign each point to the nearest mean location
    - Recalculate the k means
  - Repeat until convergence
    - Calculate some goodness of fit (e.g., minimum total distance, BIC)
  - Generally, do this for multiple different initial locations and a range of K
    - No guarantee of convergence to global optimum, only to local optimum
    - Choose the lowest BIC

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Examples

- Example 1: Palmer's Penguins
  - Known clusters (species)
- Example 2: Simulated data
  - Can investigate the impact of changes more easily with simulated data

Growth Mixture Modeling

Growth mixture modeling (GMM) is a method for identifying multiple unobserved sub-populations, describing longitudinal change within each unobserved sub-population, and examining differences in change among unobserved sub-populations.

Ram & Grimm, 2009, p. 265

- MLM
  - Not really K-means clustering, but a similar iterative process
  - Intra-class correlation: Do we need MLM?

Growth Curve K-Means Latent Classes

- Fit trajectories to some common form
  - ”Intercept-slope-quadratic”
- Cluster regression coefficients
- Fastest approach
  - Iteration over smallest number of dimensions
  - But…misses multilevel nature of GMM

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K-Means Longitudinal Latent Classes

- Cluster (time based) trajectories
- Distance: Sum of distances at each time between pairs of trajectories
  - Missing data issues
  - Scaling and centering

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Questions

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STOP

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Next session @ UTC 1900

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