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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Categorical Time Series

- Categorical v. Continuous
  - Distance, etc., don't work
  - Many tests don't work so well either
- Dynamics
  - Probabilities
- Self-organization
  - Burstiness
  - Inverse power law distribution

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State Space Grids

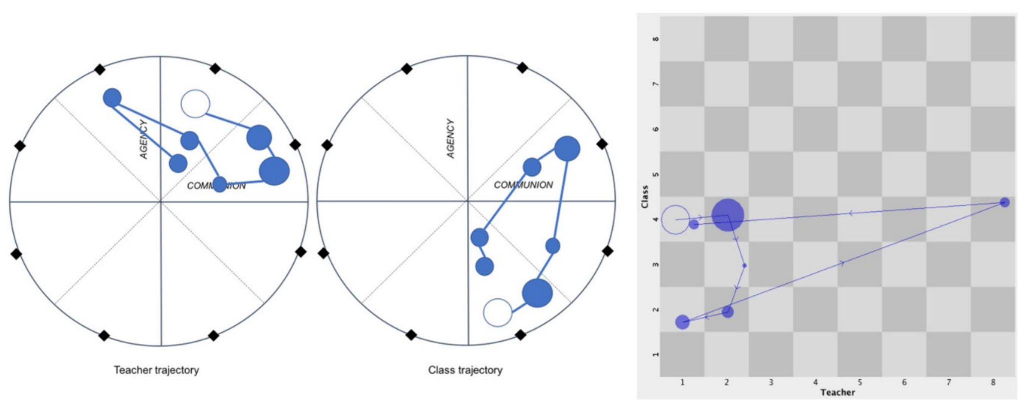

Figure 2. Example SSG. In this hypothetical example, a student-class interaction trajectory is presented. Note that the location of the dots in the IPCs and in the SSG is completely arbitrary; it does not say anything about the location of behavior in the IPC. Note that the numbers on the *x*-axis and *y*-axis correspond to the octants of the IPC-T and IPC-S (in brackets): 1 = directing (pro-active). 2 = helpful (supportive), 3 = understanding (collaborative), 4 = compliant (reliant), 5 = uncertain (withdrawn), 6 = dissatisfied (dissatisfied), 7 = confrontational (confrontational), 8 = imposing (critical).

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Markov Models

- *Markov matrix* (a.k.a, *transition matrix*)
- Dynamics: state from (immediately) prior state
  - *Memoryless*
  - Categorical data series
  - Estimation of transition probabilities
- Markov is an ancestor of language prediction algorithms
  - Allows for memory
    - More than one previous word used for prediction
    - Full corpus probabilities modified by individual’s corpus probabilities

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Create Markov Matrix From Data

- Sun, Rain, Sun, Sun, Sun, Rain, Sun, Sun, Sun, Sun, Rain, Sun, Sun, Sun, Sun, Sun, Sun, Sun, Sun, Rain
- Probabilities:
  - Rain follows Sun 4 times
  - Sun follows Sun 12 times
  - Sun follows Rain 3 times
- Count matrix and probability matrix (divide by row sum)

$$\begin{bmatrix} 12 & 4 \\ 3 & 0 \end{bmatrix} \xrightarrow{\text{yields}} \begin{bmatrix} .75 & .25 \\ 1 & 0 \end{bmatrix}$$

- Confidence intervals needed…

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Population Distribution

- Each year, we find that 80% of the people stay put. And
  - 15% of urban dwellers move to the suburbs and 5% move to rural areas
  - 10% of suburbanites move to urban areas and 10% to rural areas
  - 20% of rural dwellers move to urban areas
  - (Ignore the confidence intervals for now)
- Matrix:

$$\begin{bmatrix} 0.80 & 0.15 & 0.05 \\ 0.10 & 0.80 & 0.10 \\ 0.20 & 0.00 & 0.80 \end{bmatrix}$$

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In practice

- Data stream:
  - C, A, A, C, A, A, C, A, D, B, A, B, A, A, B, A, A, D, B, A, B, A, A, B, C, D, B, D, A, C, C, A, A, C, A, A, A, C, A, A
- Create markov matrix (with 95% CI, 100 bootstrap replications) from *markovchain::markovchainFit()*

$$\begin{bmatrix} 0.450\ (0.1560\ 0.744) & 0.200\ (0.004\ 0.396) & 0.250\ (0.031, 0.469) & 0.100\ (0.000{,}0.239\ ) \\ 0.714\ (0.088, 1.000) & 0.000\ (0.000, 0.000) & 0.143\ (0.000, 0.423) & 0.143\ (0.000, 0.423) \\ 0.750\ (0.150, 1.000) & 0.000\ (0.000, 0.000) & 0.125\ (0.000, 0.370) & 0.125\ (0.000, 0.370) \\ 0.250\ (0.000, 0.740) & 0.750\ (0.000, 1.000) & 0.000\ (0.000, 0.000) & 0.000\ (0.000, 0.000) \end{bmatrix}$$

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Why Do This?

- *If* the data are stationary
  - Long term behavior
  - First visit times
  - Return (to state) times
- All these from the eigenvalues and eigenvectors of the transition matrix
- Also: Sets us up for Hidden Markov Models (HMM)

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Example: Long-Term Behavior

- Requires stationarity in dynamics
- Find the eigenvalues and eigenvectors of the transition matrix!

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First Visit and Return Times

- Requires stationarity in dynamics

Hidden Markov Models

- Markov Models: Built on observables
- Suppose dynamics are driven by un-observables?
  - Hidden Markov Models (HMM)

HMM Toy Example

- We see 1, 2, or 3 ice creams eaten in a day
  - Model the time-series data with a Markov Chain
- What drives it?
  - It makes sense that it is whether it is hot or cold on that day.

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HMM: Weather and Mobility

- Does the weather drive mobility?
  - Categorize data
  - Can also do via SINDy

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HMM: Patient and Therapist

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HMM: Ecosystems

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Machine Learning: Preparation

- In R
  - package:caret
  - package:neuralnet
- Machine Learning is better in Python
  - package: reticulate
  - Behind the scenes: Keras and Tensorflow in Python
- Can be a pain to setup
  - Go through step by step
  - Go to Rstudio (exit and restart)

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Questions

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STOP

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Next session @ UTC 1900

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