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 I: Detecting Nonlinearity

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Seminar Overview

- Day 1
  - **Session 1: Introduction to Nonlinear Time Series (NTLS)**
  - Session 2: Behaviors and State Spaces
- Day 2
  - Session 3: State Spaces (continued)
  - Session 4: Recurrences
- Day 3
  - Session 5: Tests
  - Session 6: Singular Spectrum Analysis and Noise
- Day 4
  - Session 7: Surrogate Data
  - Session 8: Convergent Cross Mapping

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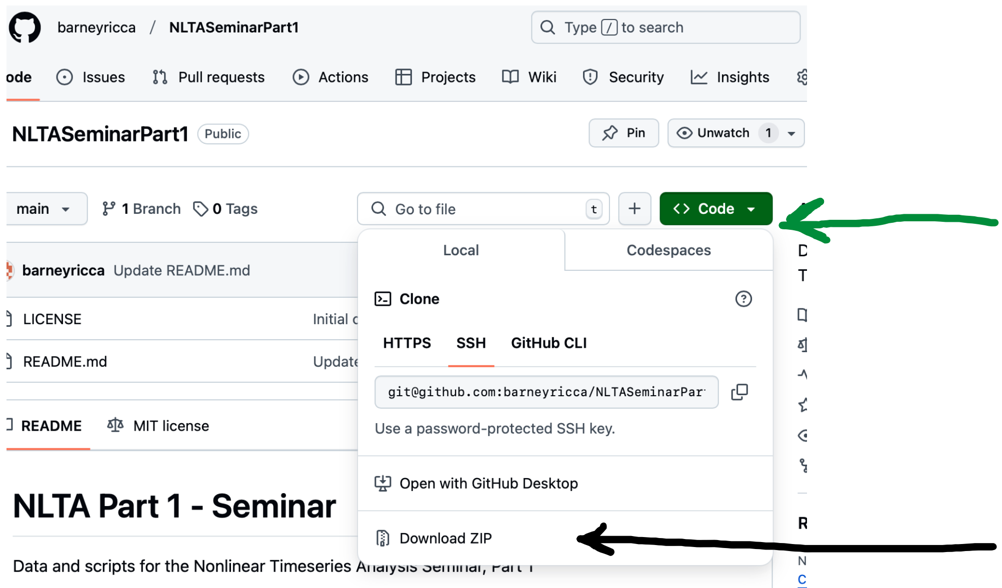
https://github.com/barneyricca/NLTASeminarPart1



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Introductions

- You
  - Location and field of interest into the chat, please
- Barney Ricca
  - ”Upstate” New York (USA)
  - Physics, computer science, statistics: Data scientist
  - STEM Education
  - Psychology (trauma and resilience)
  - Idiosyncratic R user
- The schedule
  - Should be reasonably close, but time left at the end because it won’t be…

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Scientific Endeavor

- Dance of theoretical and empirical
  - Not linear
  - Not an alternating process
  - Not tidy
- Model building
  - Box: Wrong, but useful
  - Epstein: Take away, not add
  - Models that are insightful, realistic, and practical

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Physics Envy

- Physics envy
  - “Look: these methods have been so successful for the physicists; let us apply them to our own areas of interest.” (Weinreich, 1992)
- Reduce-then-add
  - “Economists are good at reducing a complicated world to a few assumptions, then adding bells and whistles to make their models more realistic.” (The Economist, 2016)
- Rocket science
  - Easy (by comparison)
  - “It is not that other subjects…are less interesting or exciting – in some ways they may be more so – but that progress in those areas must be attempted by other methods.” (Weinreich, 1992)

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Why Nonlinear Time Series (NLTS)?

- NLTS offers an alternative to (over)simplify-then-add:
  - “NLTS facilitates well-conducted evidentiary scientific inquiry by providing a collection of mathematically rigorous procedures that help practitioners to extract information on real-world dynamics from observed data that often have a complex, highly variable and random appearance.” (HBR, p. 3)
- New tools to avoid over-simplification

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Recap: Nonlinear Dynamical Systems

- State spaces
  - Dynamics = {States, Rules}
- Fixed points & Stability
  - The structure of the state space is dependent on these.
  - Derivatives are important
- Formal models
  - Vector fields and nullclines

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Nonlinear Dynamical Systems (NDS)

- Linear paradigm
  - Separable
  - Signal + Noise
  - Changes are externally forced
- NDS Paradigm
  - Not separable
  - Stochasticity may be a signal
  - Dynamics (and changes) are internal as well as external
- New paradigm
  - New problems and new tools

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Problems

- Noisy linear can look nonlinear
- Nonstationary can look random
- Stationary nonlinear can look nonstationary

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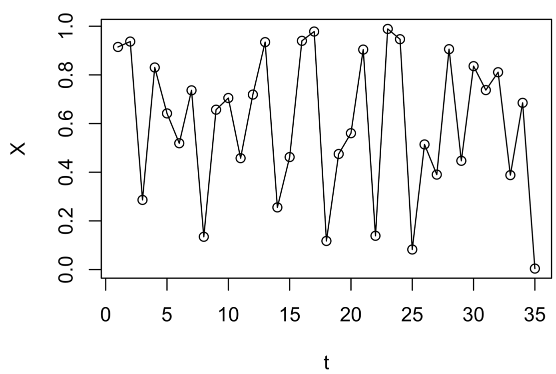
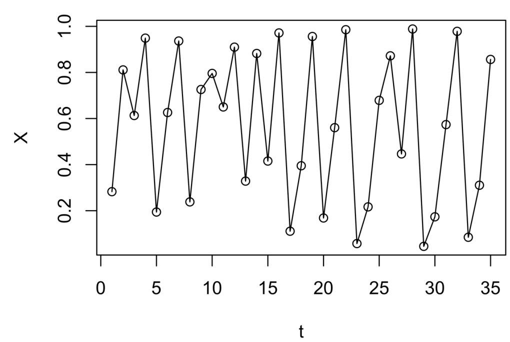
Noisy Linear





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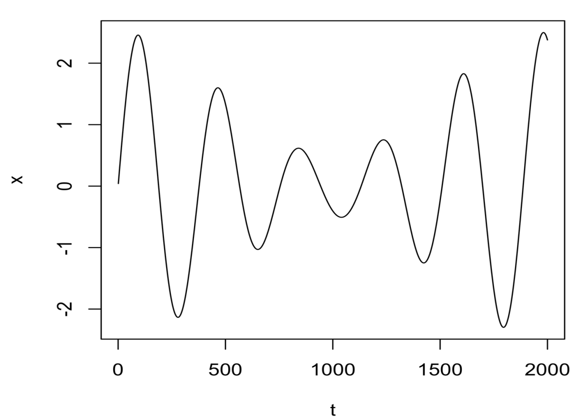
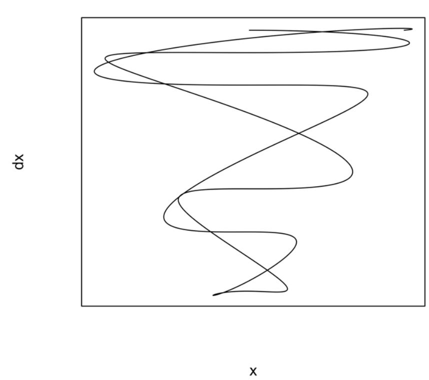
Nonstationary





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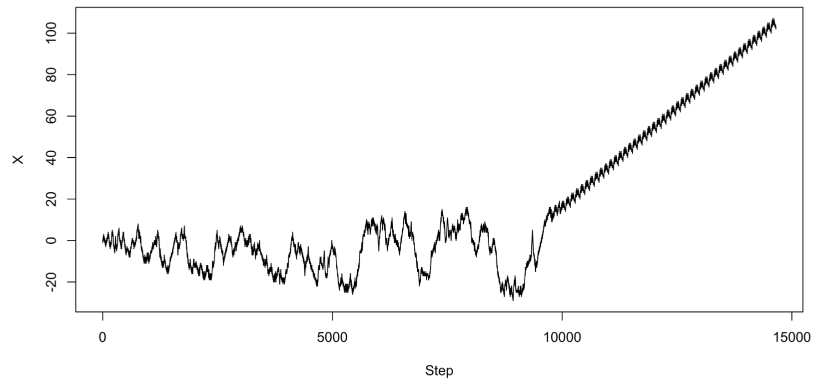
Stationary (?) Nonlinear



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What do you mean by....?

- Random noise?
  - Minimum description length
- Linear?
  - When is something with changing parameters linear?
- Endogenous?
  - Is it Langton's ant in an "environment," or is Langton's ant the {ant + environment}?
- Bateson
  - Where does a blind man with a cane end?

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NLTS Problems

- Pre-processing before modeling
- Hence, two seminars:
  - Part I (this seminar): Reconstruct topology and find the signal to model
  - Part II: Phenomenological modeling

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Overview of NLTS

- Do we detect a signal or not? (Part I)
  - Preprocess the data
- Is there a strong signal? (Part I)
  - Separate noise from signal
- Are low-dimensional nonlinear dynamics detected? (Part I)
  - State space reconstruction
- Does the signal have any hints of being causal? (Part I)
  - If so, phenomenological modeling (Part II)
  - Does the model correspond to the signal? (Part II)
  - Theory looks at correspondence

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NLTS Example #1

- We being by looking at two time series in R
  - Which of these is random and which isn't?

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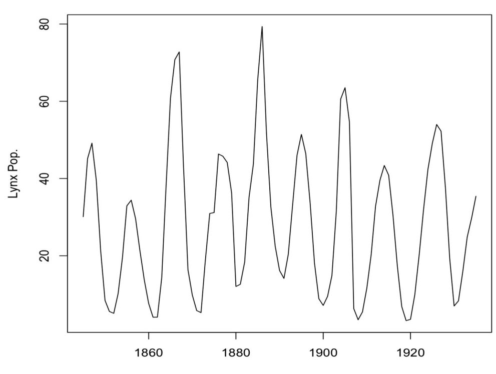
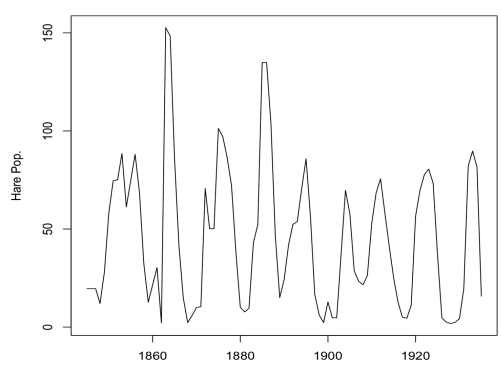
NLTS Example #2

- We now look at a 2-dimensional example, historical data of lynx and hare population
  - The *state* of this system is *(hare population, lynx population)*





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Delay State Spaces

- A.k.a.
  - Shadow state spaces
  - Reconstructed state spaces
- This blurs the line, so be careful:
  - Differences are not dynamic
    - Time-lagged, not simultaneous
  - But differences estimate derivatives
  - Differences can be used to (topologically) mimic dynamics

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Caveats and Problems

- Short data
- Noisy data
- Nonstationary data
- Interpretability of model

- Some demonstrations of these problems

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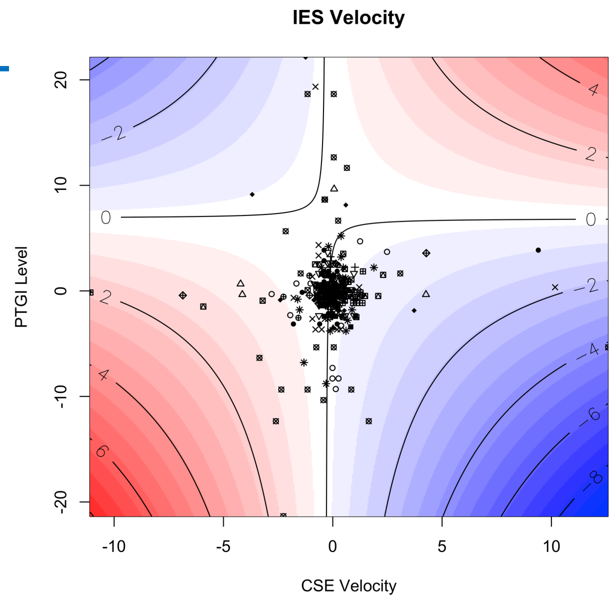
Aside: Interactions

- Model:
- $\dot{I} = \beta_1 \dot{C} P$
- Contours indicate ΔI
  - Negative IES velocity is better
  - 2nd an 4th quadrants



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Overview of Part I: Detecting Nonlinearity

- Mostly work with a single data stream
  - Everything is interdependent, so Takens will help us.
- Diagnostics & signal detection
  - State space reconstruction
  - Characterizing state space (e.g., recurrences, entropy)
  - Tests (e.g, extreme values, return-level plot, change-point detection)
- Phenomenological Modeling indicated?
  - Convergent cross mapping

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Questions

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STOP

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Next session @ UTC 1900

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