Overview of Network Models

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Network Science and Social Networks at the U (NETSNAU)

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Contents

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The question

"I have data ABC and hypotheses XYZ...

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What **method** should I use to **address these questions**?"

Modeling Networks

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Nonetheless...

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We can (and should) have a more systematic view of modeling networks and complex systems.

Modeling ~~Networks~~ Complexity (cont. 2)

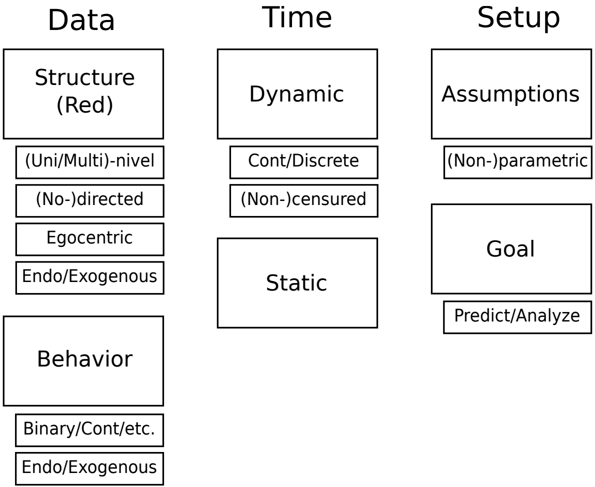

Figura: Different dimensions of SNA (a view from the data.) All components interact with each other.

Modeling Networks

Taxonomy of Methods

- Modeling Structure
- Modeling Behavior
- Modeling Structure x Behavior

More on Modeling Complexity

Taxonomy of Methods: A proposal

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Taxonomy of Methods: A proposal

Two key dimensions, **structure** vs **behavior**, in particular

- Structure: We just care about the network.
- Behavior: Behavior given the existence of a network.
- Structure x Behavior: We want to understand the co-evolution/distribution of network and behavior.

Taxon: Structure

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Non-parametric

- **Network Bootstrap** Standard errors and graph-level contrasts.
- **Network rewiring algorithms (e.g. CUG test)** *Motifs* detection conditioning on observables (e.g., sequence or degree distribution)
- **Quadratic Assignment Procedure (QAP)** Label permutation for hypothesis testing.

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Non-parametric

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Parametric

- **Exponential Random Graph Models (ERGMs)** Including all its flavors, like, TERGMs, BERGMs, ERGMitos, etc.
- **Relational Event Models (REMs) y Dynamic Actor Network Models (DyNAMs)** Sequence of interactions throughout time.

Ref: Butts (2008a, 2008b), Caimo y Friel (2014), Krackhardt (1988), Robins y col. (2007), Snijders y Borgatti (1999), Stadtfeld y Block (2017) y Vega Yon y col. (2021)

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Parametric

- **Spatial Autocorrelation**: Like Moran's I.
- **Spatial Autoregressive Models**: Like GLMs, but assuming that errors are jointly distributed in a graph-like fashion.
- **Lagged regressions** Entities' behavior is a function of previous exposure to peers.

Ref: Butts (2008a), LeSage (2008), Moran (1950) y Valente y col. (2019)

Taxon: Structure x Behavior

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Non-parametric

- **Agent-Based Models (ABM)** Simulation of Complex systems.
- **(idem)** used for parameter estimation through, e.g., likelihood-free MCMC and Approximate Bayesian Computation (ABC).

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Non-parametric

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Parametric

- **Stochastic Actor Oriented Model (SAOM)** Continuous Markov process in which individuals behavior and embeddedness interact throughout time.
- **Discrete Exponential-Family Models (DEFMs)** Individuals make multiple decisions on behavior and ties simultaneously (on development by yours truly...).

Ref: Marjoram y col. (2003), Ry y col. (2010), Snijders y col. (2010) y Tisue y Wilensky (2004)

More on Modeling Complexity

Too many other methods/themes out there:

- Modeling evolution using dynamic programming (likelihoods on directed graphs) (biology and computer science.) (Felsenstein, 1981)
- Identifying key entities in networks (centrality measures, structural holes, etc.) (Bringmann y col., 2019)
- Micro to macro behavior in Cellular Automatons. (Wolfram, 1983)
- Bayesian Networks (treating variables as nodes.) (Heckerman, 2008)
- Networks of Gene products. (Hecker y col., 2009)
- Stochastic block models (multi-group networks.) (Holland y col., 1983)
- Signed graphs (e.g., balance theory, i.e., the friend of my friend is my friend.) (Cisneros-Velarde y col., 2021)
- Survey and sampling methods for networks (e.g., snowball sampling.) (Goodman, 1961)
- Statistical mechanics of complex systems (Albert & Barabasi, 2002; Barabási & PÃ3sfai, 2016)
- ...

Thank you!

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