Modeling Network Data

seminar

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Topic of this seminar.

Statistical models for social network data.

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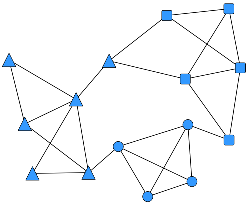
Statistical models for social network data.

Social networks consist of **actors** and **relations** among them.

- **actors:** persons, organizations, companies, countries, ...
- **relations:** friendship, asking for advice, communication, collaboration, trade, war, ...



Topic of this seminar.

Statistical models for social network data.

Statistics can formulate precise statements about **uncertainty**.

What would happen, if we measured the data again?

- at a different point in time,
- on a different set of actors,
- with different environmental factors, ...

estimate expected outcome $\pm$ **variability**

$\Rightarrow$ to explain and predict social relations and behavior.

Network models may serve several purposes.

Explaining social relations and/or behavior

- search for rules that govern the evolution of social networks.

Predicting social relations and/or behavior

- learn from given data and predict the data yet to come.

Random generation of networks that look like real data

- algorithm engineering; empirical estimation of average runtime or performance;
- simulation of network processes (e. g., information spreading, spread of disease).

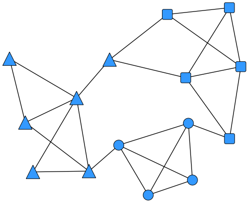
Graphs.

A *graph* is a pair $G = (V, E)$, where V is a finite set of *vertices* and E the set of *edges*.

- *undirected* graph: $E \subseteq \binom{V}{2} = \{\{u, v\}\,;\ u, v \in V\}$
- *directed* graph: $E \subseteq V \times V = \{(u, v)\,;\ u, v \in V\}$

Interpretation:

- vertices correspond to actors
- edges form the relation among them



Graphs can be **attributed** and/or **time-dependent**.

Random graph models.

A *random graph model* is a probability space $(\mathcal{G}, P)$, where $\mathcal{G}$ is a set of graphs and

$$P\colon \mathcal{G} \to [0,1]$$

a probability function, satisfying

$$\sum_{G \in \mathcal{G}} P(G) = 1 \quad .$$

(I) Exponential random graph models (ERGM).

The *ERGM class* consists of random graph models $(\mathcal{G}, P_\theta)$ whose probability function P_θ can be written as

$$P_\theta(G) = \frac{1}{\kappa(\theta)} \exp\left(\sum_{i=1}^{k} \theta_i \cdot g_i(G)\right)$$

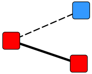
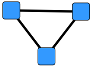
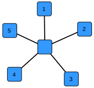
with

- $g_i \colon \mathcal{G} \to \mathbb{R}$ for $i = 1, \ldots, k$ (*statistics*);
- $\theta_i \in \mathbb{R}$ for $i = 1, \ldots, k$ (*parameters*); $\theta = (\theta_1, \ldots, \theta_k)$;
- *normalizing constant* κ defined by

$$\kappa(\theta) = \sum_{G' \in \mathcal{G}} \exp\left(\sum_{i=1}^{k} \theta_i \cdot g_i(G')\right) \quad .$$

(I) Commonly used statistics.

$$P_\theta(G) = \frac{1}{\kappa(\theta)} \exp\left(\sum_{i=1}^{k} \theta_i \cdot g_i(G)\right)$$

$g_i(G)$		**effect**
number of edges		density
edges connecting same attribute		homophily
number of triangles		transitivity
number of ℓ-stars		pref. attachment

(II) Stochastic actor-oriented models.

Models for **longitudinal** network data: networks observed at $M \geq 2$ points in time $G_1, \ldots, G_M$.

Specify probabilities $P(G_{t_i}|G_{t_{i-1}})$ for the network at time t_i given its state at the preceeding observation time t_{i-1}.

Transition from $G_{t_{i-1}}$ to G_{t_i} modeled by a stochastic process:

- at a given moment one probabilistically selected actor u has the opportunity to change;
- actor u might change one of his/her out-going ties (u, v) to maximize a random utility function

$$f_u(\beta, G(u \to v)) = \sum_{k=1}^{K} \beta_k s_{uk}(G(u \to v)) + U_u$$

The topic of this seminar are models that extend or modify one of these frameworks

making them applicable to more general network data.

Organizational points.

General information.

Project webpage:

http://www.inf.uni-konstanz.de/algo/lehre/ss13/seminar/

Participants independently get a published paper introducing a model extension or model alternative.

Participants give a presentation and write a term paper where they explain and summarize (potentially criticize) the main contribution of that paper.
Target audience/readers: your fellow students.

Requirements and timeline.

Credit requirements: term paper and presentation.

Approximate schedule:

- **(by 24 April)** topic selection;
- **(3 – 7 June)** individual meeting
  (discuss progress made so far);
- **(8 – 12 July)** individual meeting
  (outline of presentation and term paper);
- **(15 – 19 July)** **depends on number of participants**
  presentation in a plenary session
  ($\approx$ 30 minutes plus 15 minutes discussion).
- **(by 30 September)** term paper

Topics / papers.

(1) Multivariate ERGM.

Pattison and Wasserman (1999) “Logit models and logistic regression for social networks: II. Multivariate relations” *British Journal of Mathematical and Statistical Psychology* 52: 169–193.

Extension of exponential random graph models to multivariate networks (more than one relation on the same set of actors).

(2) ERGM for valued edges I.

Desmarais and Cranmer (2012) “Statistical inference for valued-edge networks: the generalized exponential random graph model” *PLoS ONE* 7(1).

Extension of exponential random graph models to valued networks (edges have associated weights).

Compare to Krivitsky (2012).

(3) ERGM for valued edges II.

Krivitsky (2012) “Exponential-family random graph models for valued networks” *Electronic Journal of Statistics* 6: 1100–1128.

Extension of exponential random graph models to valued networks (edges have associated weights).

Compare to Desmarais and Cranmer (2012).

(4) Temporal ERGM.

Hanneke, Fu, and Xing (2010) “Discrete temporal models of social networks” *Electronic Journal of Statistics*, 4: 585–605.

Extension of exponential random graph models to time-dependent networks (a network observed at two or more points in time).

Compare to Krivitsky and Handcock (2012).

(5) Separable temporal ERGM.

Krivitsky and Handcock (2012) “A separable model for dynamic networks” *Journal of the Royal Statistical Society*, in press.

Extension of exponential random graph models to time-dependent networks (a network observed at two or more points in time).

Compare to Hanneke, Fu, and Xing (2010).

(6) Adjusting ERGM for network size.

Krivitsky, Handcock, and Morris (2011) “Adjusting for network size and composition effects in exponential-family random graph models” *Statistical Methodology* 8(4): 319–339.

(7) SAOM with changing node set.

Huisman and Snijders (2003) “Statistical analysis of longitudinal network data with changing composition” *Sociological Methods & Research*, 32(2): 253–287.

Extension of stochastic actor-oriented models to networks where the set of actors (nodes) changes over time.

(8) Multivariate SAOM.

Snijders, Lomi, and Torlo (2012) “A model for the multiplex dynamics of two-mode and one-mode networks, with an application to employment preference, friendship, and advice” *Social Networks*, in press.

Extension of stochastic actor-oriented models to multiple networks on the same set of actors.

(9) Event networks.

Butts (2008) "A relational event framework for social action" *Sociological Methodology* 38(1): 155–200.

Models networks given by dyadic, time-stamped interaction events, such as emails or phone calls.

(10) Egocentric event network.

Vu, Asuncion, Hunter, and Smyth (2011) “Dynamic egocentric models for citation networks”. In: *Proceedings of the International Conference on Machine Learning*.

Models event networks in a different way than Butts (2008).

(11) Multilevel network model.

Zijlstra, van Duijn, and Snijders (2006) "The multilevel p_2 model" *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences* 2(1): 42–47.

Model for collections of several networks.

(12) Algebraic constraints.

Pattison, Wasserman, Robins, and Kanfer (2000) "Statistical evaluation of algebraic constraints for social networks" *Journal of Mathematical Psychology*, 44: 536–568.

Analyzes networks with multiple relations by searching for *algebraic constraints* among given or compound relations.