

Models of Friendship Formation for the Generation of Synthetic Social Networks

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Introduction

Inspiration for the Current Model

New Model

Conclusions

What this Presentation is

- ▶ Presentation of Work In Progress
- ▶ Development of models of friendship formation
- ▶ Aim: *generating* social networks
- ▶ Based on previous work by Matthias Kowald and Theo Arentze
- ▶ Criticism Welcome!
 - ▶ Probability that I missed some important detail significantly different from 0

Introduction

- ▶ Social contacts and their distribution assumed to have important impact on where leisure activities are performed
- ▶ If it is the case, social network data might help in forecasting
- ▶ Important characteristic of social networks:
 - ▶ Spatial distribution of social contacts
 - ▶ Homophily
 - ▶ Degree distribution
 - ▶ Transitivity/Clustering
- ▶ Generating synthetic social networks:
 - ▶ Reproduce important characteristics
 - ▶ Be computationally *scalable*
 - ▶ aim: generate network for synthetic Swiss population

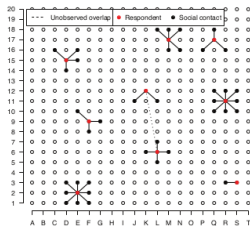
A Word on the Data

- ▶ Vocabulary:
 - ▶ ego: person of interest
 - ▶ alter: (potential) friend of an ego
 - ▶ tie: existence of a relationship of interest
 - ▶ social network: graph where nodes are egos and edges are ties
 - ▶ ego-centric network: graph composed by one ego and its alters
 - ▶ clustering: proportion of possible triangle that are closed
 - ▶ “friends of friends that are friends”
- ▶ Assume we have a way to reveal (sub) network
- ▶ Static view
- ▶ In our case: snowball sample
 - ▶ Focus on *leisure contacts*
 - ▶ assumption: all relevant ties are reported (not in the dataset ⇒ not in the real world)

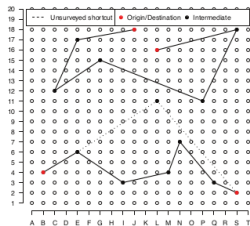
Snowball Sampling

Source: Kowald (2013)

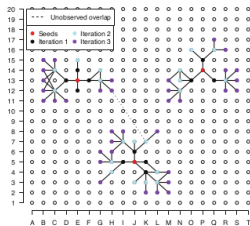
1a: Isolated personal networks



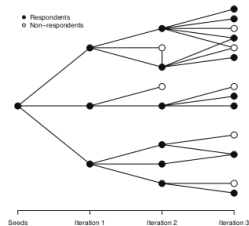
1b: Small-world experiment



1c: Snowball sampling



1d: Snowball sampling schema



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Inspiration: T. Arentze *et Al.* 2013

- ▶ Estimated on the Zurich Snowball Data
- ▶ Designed for the same purpose as here
- ▶ Only tested for a small synthetic population
- ▶ Requires calibration

Idea

- ▶ Associate a random utility to each potential tie
- ▶ The probability for a friendship to exist is the probability that this utility is higher than a fixed threshold

$$P(ij) = P(U_{ij} + \varepsilon_{ij} > u_0)$$

- ▶ Threshold is lower in case of common friends

$$P(ij) = P(U_{ij} + \varepsilon_{ij} > u_0 - \Theta)$$

- ▶ transitivity
- ▶ U_{ij} symmetric, and contains distance and homophily measures

Pros and Cons

- ▶ Pros
 - ▶ ε_{ij} logistically distributed leads to closed form likelihood
 - ▶ basically a “yes/no” logit for each tie
 - ▶ each tie can be considered in (almost) isolation for estimation
 - ▶ intuitive two-rounds generation algorithm
- ▶ Cons
 - ▶ Degree increases with size of the “choice set”
 - ▶ thresholds u_0 and Θ need to be calibrated to reproduce average degree and clustering
 - ▶ Diversity of chosen friends decreases with size of the choice set
 - ▶ in particular spatial distribution!

Results

Soc. Net.	Clust.	Avg. Deg.	Homophily		Dist.
			Age	Gender	
Snowball	0.206	22	46.3%	61.7%	26.6 km
0.025%	0.190	22	30.7%	56.5%	49.1 km
0.025% (ZH)	0.187	20.6	29.4%	55.7%	17.8 km
10%	0.150	21.7	45.2%	66.0%	18.8 km
10% (ZH)	0.225	20.6	45.4%	66.2%	7.3 km

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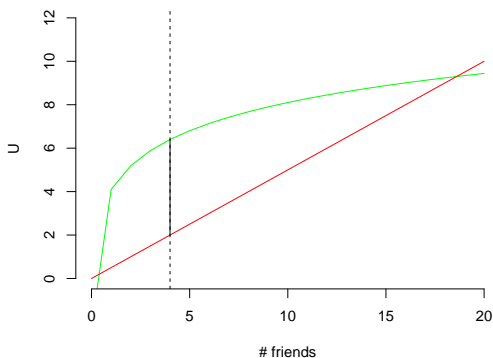
New Model

- ▶ Aim: try to overcome the Cons
 - ▶ (leads to dropping some Pros...)
- ▶ Basic Idea:
 - ▶ friends come with a utility (they are nice) and a cost (but they cost time)
 - ▶ “marginal utility” of an additional friend decreases with number of friends
 - ▶ individuals balance utility and cost
 - ▶ possible cost functions:
 - ▶ linear in ego-centric network size
 - ▶ linear in number of *cliques*
 - ▶ “multiple discreteness” formulation

Natural Formulation

- ▶ Basic decision rule: ego e choses the ego-centric network \mathcal{N} that maximizes

$$\log \left(\sum_{i \in \mathcal{N}} U_{ei} \right) - \mathcal{C}(\mathcal{N})$$



Problems

- ▶ In this general form, combinatorial
- ▶ might be possible to make estimable/simulable by additional hypotheses. . .

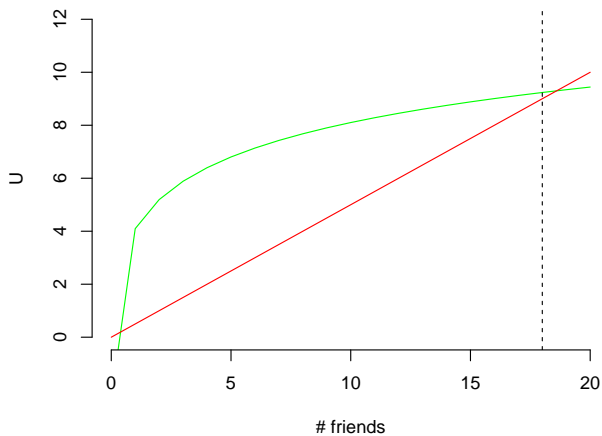
Alternative Formulation

- ▶ Basic decision rule: ego e accepts any tie as long as resulting ego-centric network \mathcal{N} satisfies

$$\log \left(\sum_{i \in \mathcal{N}} U_{ei} \right) \geq \mathcal{C}(\mathcal{N})$$

- ▶ for estimation: likelihood of a tie is its probability of acceptance *given the rest of the ego-centric network*
- ▶ for simulation:
 - ▶ simulate the utilities
 - ▶ greedy algorithm: grow the network until no improvement is possible
 - ▶ select all remaining agents in the “choice set” that fulfill the condition
 - ▶ take one at random
 - ▶ should work if $\mathcal{C}(\mathcal{N})$ grows with $|\mathcal{N}|$

Intuition



Likelihood: Probability of a Tie

- ▶ Consider each tie independently
 - ▶ non-realized ties as well
- ▶ $U_{ea} = U_{ae} = V_{ea} + \varepsilon_{ea}$
- ▶ ego e accepts tie ea if

$$\varepsilon_{ea} > \exp(\mathcal{C}(\mathcal{N}_{+ea}^e)) - \sum_{i \neq a} U_{ei} - V_{ea} = \Theta_{ea}$$

- ▶ we know the existing network, so we know

$$\sum_{i \neq a} U_{ei} > \exp(\mathcal{C}(\mathcal{N}_{-ea}^e)) = \Theta_{-ea}$$

- ▶ The probability $P(ea)$ to observe a tie ea is:

$$P \left(\varepsilon_{ea} > \max(\Theta_{ea}, \Theta_{ae}) \mid \sum_{i \neq a} U_{ei} > \Theta_{-ea}, \sum_{i \neq e} U_{ai} > \Theta_{-ae} \right)$$

Estimation

- ▶ No chance of getting a closed form here
- ▶ Assume $\varepsilon \sim \mathcal{N}(0, 1)$. Then the sum of n realizations follows $\mathcal{N}(0, n)$
- ▶ For each tie, can simulate $P(ea)$ (resp. $P(\neg ea)$):
 - ▶ Sampling $\sum_{i \neq a} U_{ei}$ from truncated normal distribution
 - ▶ Inject resulting Θ_{ea} in $1 - \text{CDF}$
 - ▶ Average
 - ▶ Likelihood: $\prod_{ea \in \text{obs}} P(ea) \prod_{ea \in \neg \text{obs}} P(\neg ea)$
- ▶ First results
 - ▶ use R and `maxLik` package
 - ▶ First estimation still running. . .
 - ▶ Quite expensive computationally
 - ▶ Generation: Java code from the Arentze approach largely usable

Pros and Cons

- ▶ Pros
 - ▶ each tie can be considered in (almost) isolation for estimation
 - ▶ intuitive generation algorithm?
 - ▶ no calibration?
 - ▶ degree should be relatively stable with choice set size
 - ▶ diversity of generated social networks should be relatively stable
- ▶ Cons
 - ▶ no closed form likelihood
 - ▶ others to discover...

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Conclusions

- ▶ Design of a Model to generate social networks
- ▶ Existing model works, but has important flaws
- ▶ Tradeoff between elegance and usability
- ▶ Actual interest of the model still to be tested. . .