

(Multiple) Imputation in Relational Event History data: Missingness in Time, Sender, and/or Receiver

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Research aims:

- 1) To what extent does missingness in REH data (time, sender, and/or receiver of communications) introduce bias and
- 2) To what extent does imputation of missing values alleviate bias?

INTRODUCTION

- ➤ Widespread occurrence of missingness in social network analysis (SNA)
- ➤ Incomplete data, resulting from the exclusion of nodes (actors) or edges (associations) between nodes
- ➤ SNA typically from 'static' snapshots of networks
- → A new type of dynamic SNA developed Relational Event History (REH)
- **→** REH contains
 - Timestamps of when interaction took place + Dyad of sender and receiver
- → Why analyze missingness in REH?
 - → High resolution and precise network data
 - → Increasingly available but little to no research on the missingness problem
- → Missingness simulation and imputation in time, sender and/or receiver
- → Part of Apollo 13 communications among ground control and astronauts
 - → 3882 relational events (communications) among 16 nodes (actors)
 - → Missingness and imputation simulated 100 times
- → Fully observed ('truth') & complete case analysis & imputed simulation
 - → Check bias, coverage rate (CR) and absolute width (AW) compared to truth

Figure 1. Table 1. Relational events of Apollo 13 data Network graph Apollo-13 data S-ID R-ID Time 11849.2 18 18 11854.2 50012.8 13 50014.8

THEORY AND APPROACH

Relational Event Model (REM)

- ➤ Framework to model REH data
 - ➤ Events occurs in discrete moments
 - → Ties exists for short moments
 - Understanding of order and duration of events
- ➤ Enables estimation of what dyad will communicate and when future communication occurs (event rate) in log-linear function:

$$log \lambda(s,r,t) = \sum \beta_p X_p(s,r,t)$$

- \rightarrow β_p refers to the impact of the p-th statistic $X_p(s,r,t)$ on the event rate.
- Endogenous statistics (past communication)
 - ➤ Include past communication in determining event rate
 - **→** Reciprocity
 - ➤ In-degree sender
 - Out-degree receiver
- Exogenous statistics
 - → Include external factors in determining event rate
 - **→** Same location

Not data-dependent (NDD) Missingness

- → Missingness not related to observed/unobserved characteristics of the data → random missingness across data
- → Most convenient missingness mechanism
- → Benchmark for more complex context (SDD, UDD)

(Multiple) Imputation

- → Missing 'time' interpolated with single imputation
- → Missing in sender and receiver multiple imputed
 - replacement of a missing value by a plausible one multiple times and pooling the results

RESULTS DISCUSSION

Fully Observed Data - TRUTH

- → In-degree sender ($\theta = 4.31^{-04}$, p < .001) and same location ($\theta = -.86$, p < .001) statistically significant predictors of event rate
- Reciprocity ($\theta = 2.33^{-02}$, p = .209) and out-degree receiver ($\theta = -9.02^{-05}$, p = .225) not
- Those who receive more communications more likely to initiate contact, and communication more likely to take place between nodes in different location

Complete Case Analysis

 \rightarrow Overestimated reciprocity ($\theta = 2.77^{-02}$) and in-degree sender ($\theta = 5.68^{-04}$) and underestimated out-degree receiver ($\theta = 1.21^{-04}$) and same location ($\theta = -1.35$) but <u>no</u> change in statistical significance

Imputed Simulations

- Less bias BUT...
- → False statistically significant
 - **→** Reciprocity
 - → Out-degree receiver
- SE CR Bias PB Statistic $1.076^{-03} < .001 .75$ 2.52^{-02} 1.83^{-03} 7.87 Reciprocity 9.946⁻⁰⁶ < .001 .88 -1.37⁻⁰⁵ 3.31 4.18^{-04} ID sender 4.053⁻⁰ < .001 .89 -2.89⁻⁰⁶ 4.52 -9.31^{-05} OD receiver $1.181^{-02} < .001 .17$ Same Location -.91 -4.76^{-02} 5.52

- - ➤ Various sensitivity analyses (other interpolation methods for time and 'same location' data in imputation yielder similar conclusions
 - → Imputation led to better estimates of effect sizes
 - → However, small standard errors led to false statistically significant results and suboptimal coverage rates

Limitations and directions for research

- Time interpolated and imputed as single value
- Content of communication is overlooked
- Convenient NDD-mechanism for missingness
- ➤ Samples drawn from a finite population (Apollo 13 data)
 - → No sampling variance resulting in smaller standard errors
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