

Network Modeling for Epidemics

DYNAMIC NETWORK MODELS: DATA

NME WORKSHOP

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STERGMs: Data sources

1. Multiple cross-sections of complete network data

- easy to work with
- but rare-to-non-existent in infectious disease epi
- 2. One snapshot of a cross-sectional network (census, egocentric, or otherwise), plus information on relational durations
 - much more common
 - but introduces some statistical issues

Egocentric data in ERGMs and STERGMs

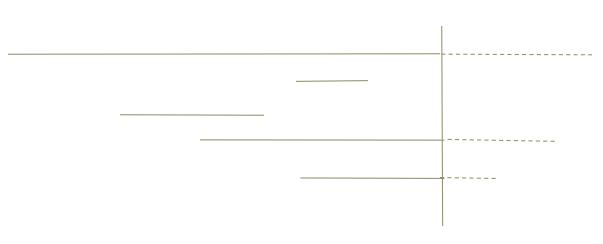
Repeating previous session:

- This approach entails constructing an 'artificial population'
 - Simulated population size does not need to match sample size (or even size of target population)
 - Don't need to be able to ID whether different respondent's partners are the same as one another, or are also respondents
 - We will go through simple examples in the tutorial today, delve back into this tomorrow

Typically takes the form of

- asking respondents about individual relationships (either with or without identifiers).
- Often this is the *n* most recent, or all over some time period, or some combination (e.g. up to 3 in the last year)
- asking whether the relationship is currently ongoing
- if it's ongoing: asking how long it has been going on (or when it started)
- if it's over: asking how long it lasted (or when it started and when it ended)
- From this we want to estimate
 - the mean duration of relationships
 - perhaps additional information about the variation in those durations (overall, across categories of respondents, etc.)

Issues?



1. Ongoing durations are right-censored

• can use Kaplan-Meyer or other techniques to deal with

Issues?

2. Relationships are subject to length bias in their probability of being observed

- This can also be adjusted for statistically
- However, complex hybrid inclusion rules (e.g. most recent 3, as long as ongoing at some point in the last year) can make this complicated

- In practice (and for examples in this course), we sometimes rely on an elegant approximation based on the properties we just witnessed:
 - If relation lengths are approximately exponential/geometric, then the effects of length bias and right-censoring cancel out
 - The mean amount of time that the **ongoing** relationships have lasted until the day of interview (relationship age) is an unbiased estimator of the uncensored mean duration of relationships
 - Yes, it's true.

- If you have something approximating a memoryless process for relational duration, then an unbiased estimator for relationship length is to:
 - ask people about how long their ongoing relationships have lasted up until the present
 - take the mean of that number across respondents.

- In practice, we find that the geometric distribution doesn't often capture the distribution of relational durations overall.
- But, if you divide the relationships into 2+ types, it can do a reasonable job within type
- Especially if you remove any 1-time contacts and model them separately (for populations where they are common)
- In our applied models (and in EpiModelHIV) we have three types
- Remember: most commonly used versions of DCMs model pretty much everything as a memoryless process, so approximating one aspect of our model that way is well within common practice

- When we pass our data into EpiModel as cross-sectional structure + durations, the algorithm is going to:
 - Calculate the dissolution coefficients first using data on duration
 - Then estimate the formation model condition on the dissolution model, using data on cross-sectional network structure

	Prevalence ≈	Incidence x	Duration
Data we have	Cross- sectional structure		Duration
Processes to model		Formation	Dissolution

Mostly this will happen behind the scenes, but to get a flavor:

 $logit \left(P(Y_{ij,t+1} = 1 | Y_{ij,t} = 1, rest of the graph) \right) = \theta^{-\prime} \partial (g^{-}(y))$

For the ~edges model, with mean duration = 90 time steps:

$$ln\left(\frac{P(\text{tie persists})}{P(\text{tie dissolves})}\right) = \theta^{-\prime} \partial\left(g^{-}(y)\right) \qquad ln\left(\frac{1-1/90}{1/90}\right) = \theta$$
$$ln\left(\frac{P(\text{tie persists})}{P(\text{tie dissolves})}\right) = \theta$$
$$ln\left(\frac{90-1}{1}\right) = \theta$$
$$ln(90-1) = \theta$$
$$4.49 = \theta$$

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- So dissolution can be solved analytically
- Then we want to condition the formation model on the dissolution model
- In R, the standard notation for indicating the parameters of a model that are to be fixed and conditioned on, rather than estimated, is with:

~offset(FixedParameter)