Small network statistics for the network science of teams[1]

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[1]Contact: vegayon@usc.edu. We thank members of our MURI research team, USC's Center for Applied Network Analysis, Andrew Slaughter, and attendees of the NASN 2018 conference for their comments.

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Network Science of Teams
a Multidisciplinary University Research Initiative

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Context: A tale about social abilities and team performance

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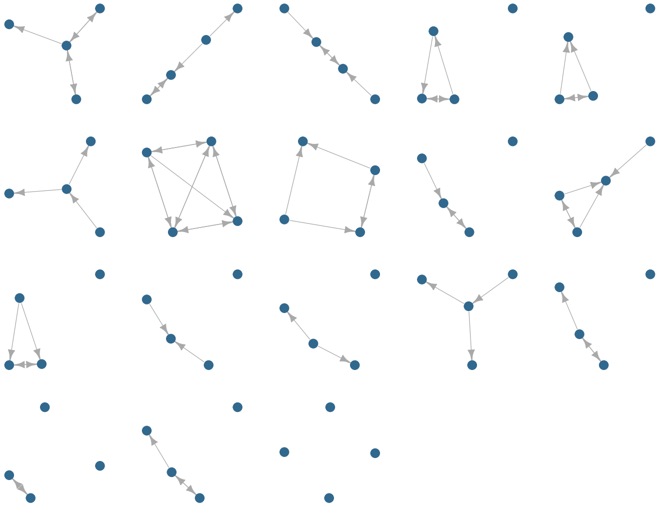
Study motivation

- Overall, a very limited set of SI domains have been tested as predictors of social networks
- Very little research on the emergence of networks in teams.

Context (cont'd)



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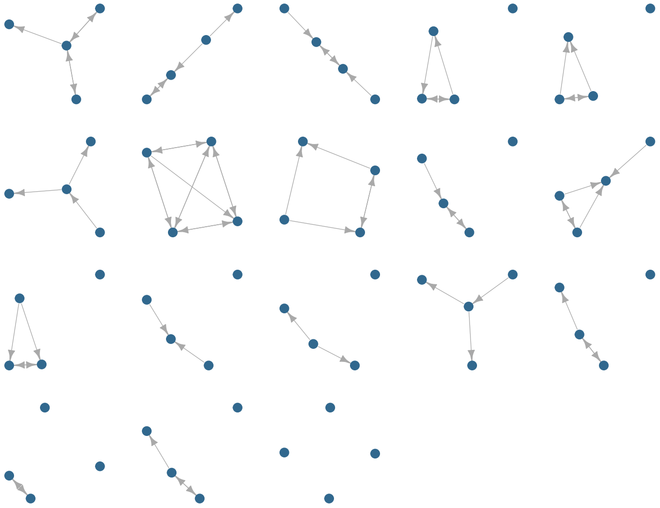
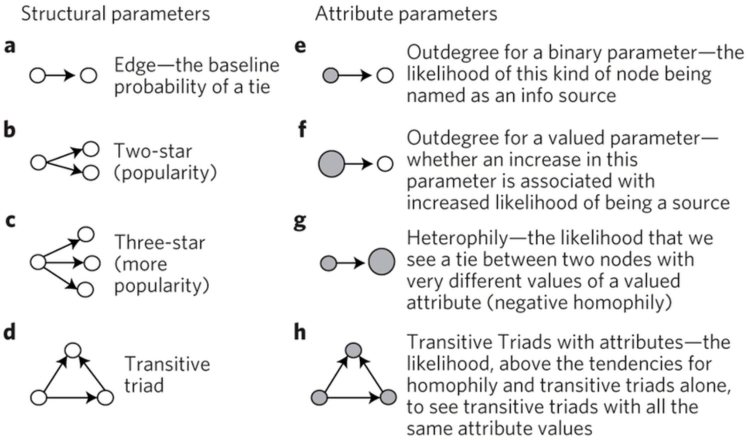


How can we go beyond descriptive statistics?

Small networks and Exponential Random Graph Models

Exponential Random Graph Models: What are the structures that give origin to a given observed graph?



(In general, ties are not IID, moreover, the entire graph is a single observation.)

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When trying to estimate ERGMs in little networks

- MCMC fails to converge when trying to estimate a block diagonal (structural zeros) model,
- Same happens when trying to estimate an ERGM for a single (little) graph,
- Even if it converges, model degeneracy, i.e. bad fit, arises too often.

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$$\Pr\left(\mathbf{Y}=\mathbf{y}|\theta,\mathcal{Y}\right)=\frac{\exp\theta^{\mathsf{T}}\mathbf{g}(\mathbf{y})}{\kappa\left(\theta,\mathcal{Y}\right)},\quad \mathbf{y}\in\mathcal{Y}$$

  Where $\mathbf{g}(\mathbf{y})$ is a vector of sufficient statistics, $\theta\in\Theta$ a vector of model parameters, and $\kappa\left(\theta,\mathcal{Y}\right)$ is the normalizing constant (a summation with $2^{n(n-1)}$ terms)

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- This solves the problem of been able to estimate a small ergm.
- For this we started working on the `lergm` R package (available at https://github.com/muriteams/lergm):

Example 1

Let's start by trying to estimate an ERGM for a single graph of size 4

```
library(lergm)
set.seed(12)
x <- sna::rgraph(4)
lergm(x ~ edges + balance + mutual)
```

```
##
## Little ERGM estimates
##
##  Coefficients:
##    edges  balance   mutual
## -1.9443  -0.2417   3.4961
```

- Cool, we are able to estimate ERGMs for little networks! (we actually call them ~~lergms~~ ERGMitos[2]),

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- Cool, we are able to estimate ERGMs for little networks! (we actually call them ~~lergms~~ ERGMitos[2]),
- Going directly to MLE, we avoid the degeneracy problem.
- Moreover, due to the size of the networks, we can actually go further and estimate pooled ERGMs

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$$

- By estimating a pooled version of the ERGM we can increase the power of our MLEs.
- We implemented this in the `lergm` package

Example 2

Suppose that we have 3 little graphs of sizes 4, 5, and 5:

```r
library(lergm)
set.seed(12)
x1 <- sna::rgraph(4)
x2 <- sna::rgraph(5)
x3 <- sna::rgraph(5)

lergm(list(x1, x2, x3) ~ edges + balance + mutual)
```

```
##
## Little ERGM estimates
##
##  Coefficients:
##    edges  balance   mutual
## -0.3941  -0.2085   1.4156
```

Simulation study

Scenario A

1. Draw parameters for edges and mutual from a uniform(-3, 3).
2. Using those parameters, sampled $n \sim \text{Poisson}(30)$ networks of size 4
3. Estimated the pooled ERGMs using both the MLE and the bootstrap version.

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Scenario B

1. Idem.
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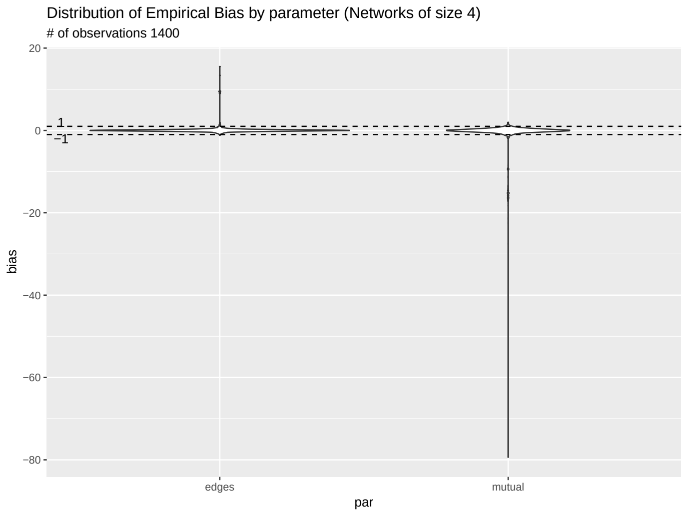
(If anyone asks, I just ran about 3 million ERGMs... :))

Simulation study: Scenario A

Empirical Bias



Simulation study: Scenario A

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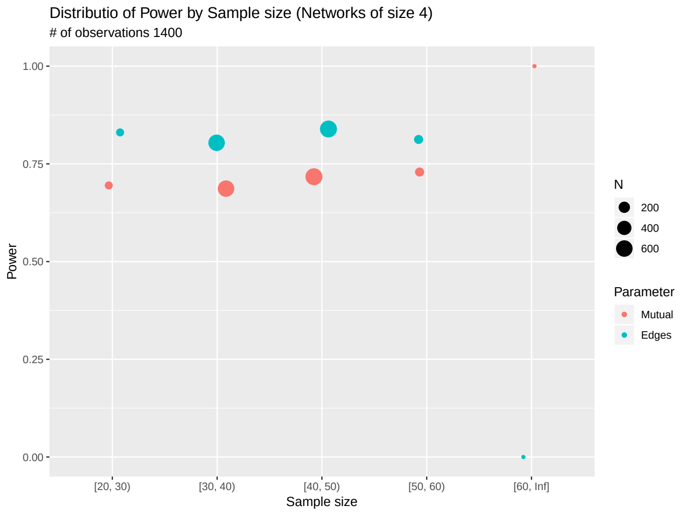
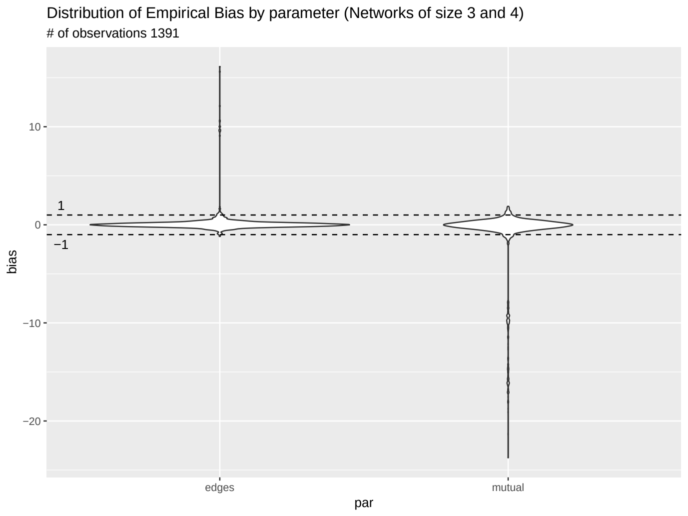


Simulation study: Scenario B

Empirical Bias



Simulation study: Scenario B

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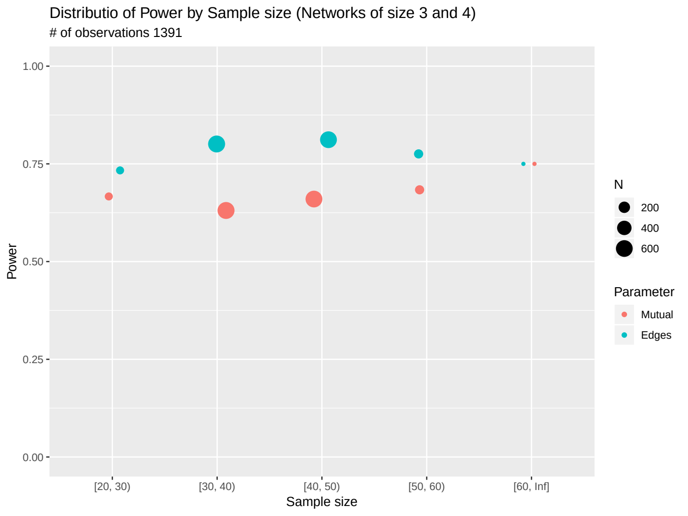
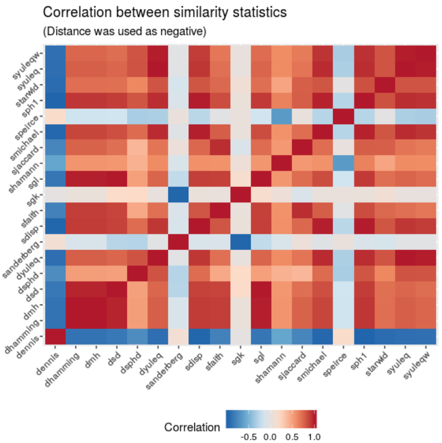


Other approaches



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- Small structures imply a smaller pool of parameters (which is OK), but can be more useful when including nodal attributes.
- When estimating the pooled version, we are essentially hand-waving the fact that parameter estimates implicitly encode size of the graph, i.e.

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- Finally, this work can be extended to other types of small networks, including: families, ego-nets, etc. And other methods, such as TERGMs.

Thank you!

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What have we got so far?

```
lergm(networks ~ mutual + edges + triangle + nodematch("male") +
    diff("Empathy") + nodematch("nonwhite"))
```

Table 1: Preliminary results with our small teams data. The table shows 95% confidence intervals for the parameter estimates using the pooled ERGM model.

	All (42)		All but size 3 (35)	
	2.5 %	97.5 %	2.5 %	97.5 %
mutual	-0.40	0.55	-0.45	0.55
edges	-0.91	-0.16	-1.04	-0.29
triangle	0.06	0.24	0.09	0.27
nodematch("male")	-0.36	0.31	-0.34	0.36
diff("Empathy")	0.12	0.59	0.09	0.58
nodematch("nonwhite")	-0.26	0.37	-0.29	0.35