Examining the Links between the Empirical and the Computational: Measuring Baseline Change in Empirical Governance Networks using Agent-Based Modeling

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Agent-Based Modeling in the Policy Sciences

- There is a growing use of Agent-Based Models (ABMs) in Public Policy and Public Administration (Axelrod, 1997; Lempert, 2002; Janssen and Ostrom, 2006; Zia and Koliba, 2012; Choi and Robertson, 2014; Maroulis and Wilensky, 2014)
- They are typically built by applying generative social science (Epstein, 2006)
- A strength of modeling is its improved ability to forecast, but the lack of calibration with empirical data inhibits this approach.



Agent-Based Modeling of Governance Networks

- Modeling the behavior of systems allows us to anticipate the response of those systems to interventions in the system
- In a policy context, this means that we can model the impact of policies to forecast their outcomes
- Agent-Based models allow for building agents who act independently and so can model emergent behavior
- Existing research applies empirically-based rules to generated populations; we use empirical populations



Drivers of Change in Networked Systems

- Baseline Change
 - On-going change from network dynamics
 - Network link accretion and decay

- Intervention-Driven Change
 - Responses to intervention
 - Behavioral changes



Link Accretion

- Homophily
- Heterophily
- Transitivity
- Exponential Random Graph Models (ERGMs)

$$P(\mathbf{Y} = y | n \text{ actors}) = \frac{\exp\left(\sum_{k=1}^{K} \Theta_k z_k(y)\right)}{c}.$$

Source: Goodreau, Kitts, and Morris (2009)



Link Decay

- Basic decay rates: Burt (2000)
 - Linear relationship across time
 - Rate affected by homophily
- Network Bridge decay rates: Burt (2002)
 - Non-linear relationship across time
 - Initially more robust than non-bridge but decay rate increases with age of tie before leveling off



Data

- Two instances of a survey of the Vermont Farm to Plate Network (2012, 2014)
- Three subnetworks
 - Information Sharing
 - Project Collaboration
 - Resource Sharing
- "New" and "Existing" ties
- Node Attributes
 - Capacity
 - Sector
 - Jurisdiction
 - Jurisdictional Level

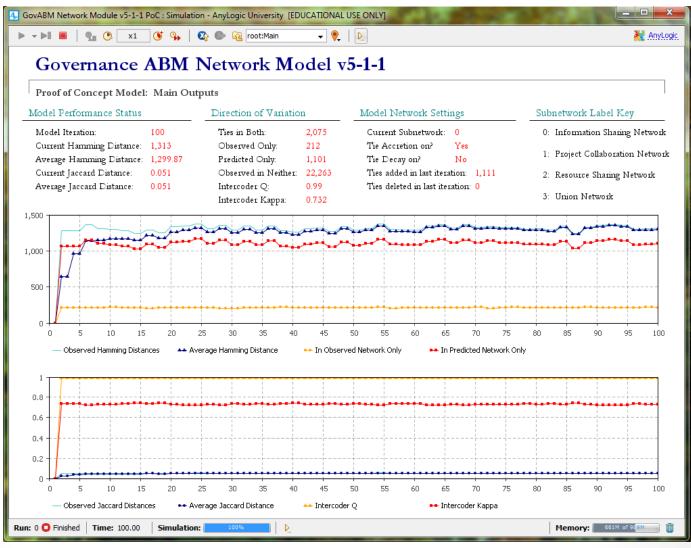


Data Profile

Subnetwork	Year	Number of Nodes	Number of Ties (New and Existing)	Density
Information Sharing	2012	219	2,612	0.055
Collaboration	2012	219	1,133	0.024
Resource Sharing	2012	219	378	0.008
Union	2012	219	2,859	0.060
Information Sharing	2014	294	2,766	0.064
Collaboration	2014	294	1,663	0.039
Resource Sharing	2014	294	881	0.021
Union	2014	294	3,378	0.078
Intersection (2012/	2014)	177		



Forecasting "New" Ties (2012 Data): Output Splash



Forecasting "New" Ties (2012 Data)

Subnetwork	Ave. Hamming Distance	Ave. Jaccard Distance	Links in Both	Links in Observed Network Only	Links in Predicted Network Only	Links in Neither
Information Sharing	1,299.87	0.051	2,075	212	1,101	22,263
Collaboration	613.8	0.024	892	118	502	24,139
Resource Sharing	835.56	0.033	300	45	799	24,507
Union	864.27	0.034	2,242	231	642	22,536



Forecasting Future Ties (2012 Data → 2014 Data)

Subnetwork	# Times Reviewed	Ave. Ham. Distance	Ave. Jac. Distance	Both	Observed Only	Predicted Only	Neither
InfoShare	2	2,304.72	0.148	218	1,082	1,246	13,030
Collab	2	1,017.72	0.065	68	692	336	14,480
ResShare	2	1,015.74	0.065	21	348	678	14,529
Union	2	2,484.90	0.160	248	1,325	1,185	12,818
InfoShare	1	2,134.44	0.138	204	1,096	1,060	13,216
Collab	1	972.18	0.063	89	671	311	14,505
ResShare	1	771.21	0.050	22	347	432	14,775
Union	1	2,210.67	0.142	273	1,300	933	13,070



Conclusions

- Model performs very well for near-term (same time period) prediction
- Model performs less well, though still satisfactorily, over two time periods
 - Error rate is higher in denser networks
 - Model is accurate in predicting number of ties, though less accurate in predicting tie location
- Improved performance when 2 years are treated as one timeslice



Implications

- Experimental control of baseline change is needed to separate out baseline change from intervention-driven or shock-driven change
- The effective modeling of baseline change provides experimental controls for experimentation using ABMs
- This model provides a platform for experimentally exploring the potential impacts of policy interventions and system shocks on governance networks.



Questions?

Thank you!







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AND

