Network Dependence in the Diffusion of Public Policies

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Patterns of Policy Diffusion

- Does adoption by one unit influence adoption by other units?
- Measured one policy at a time.
- Research on the U.S states monadic and uses contiguity;
- IR research more frequently dyadic and more nuanced.
Our Approach

1. Generate the latent diffusion network for a given set of units and a large collection of policies: does unit B tend to follow unit A?
2. Estimate the features of the resulting network using a TERGM.
3. This allows us to:
   1. Test for common monadic and dyadic predictors of diffusion ties.
   2. Theorize about and test for network-level influences on diffusion tie formation.
Mechanisms of Diffusion in Networks: Nodes & Dyads

1. Competition:
   - Usually measured by contiguity (+) or distance (−).

2. Coercion:
   - Mostly IR: measured by relative power or hegemony (+).

3. Learning:
   - Nodes: Those with resources tend to lead (+), those without tend to follow (−).

4. Emulation:
   - Nodes: those with resources tend to lead (+), those without tend to follow (−);
   - Dyads: similar nodes emulate each other, a.k.a. homophily (+).
Mechanisms of Diffusion in Networks: Network Effects

1. Competition:
   - Should be mutual, so Reciprocity (+).

2. Coercion:
   - Should be one way, so Reciprocity (−).

3. Learning:
   - Should be based on similarity, so Reciprocity (+);
   - Can flow downstream, so transitivity (+).

4. Emulation:
   - Reciprocity (−);
   - Goes from popular to less popular, so Out-degree (+) and In-degree (−).
Latent Network Estimation via NetInf

- **NetInf** (Gomez-Rodriguez, Leskovec and Krause 2010) evaluates:
  - How frequently state B adopts a policy soon after state A;
  - How frequently B adopts a policy not yet adopted by A;
  - How many other states regularly adopt between A and B that could explain B’s adoption.

- We utilize the **NetInf** package (Linder and Desmarais 2017) for estimation. This involves:
  - Setting the maximum number of edges;
  - Choosing the window of time \(K\) to include for each network;
  - Repeatedly estimating the latent network at time \(t\) including adoptions from the last \(K\) years.

- We obtain a time series of directed networks that indicate in each year whether over the last \(K\) years policies have tended to diffuse from A to B for all pairs.
Latent Networks Estimated

- **U.S. states**: SPIID data covering over 700 policies from 1860-1945.
  - We set the number of edges at 800 per year (2450 possible).
  - Optimal window is 100 years.
  - We therefore obtain networks for 1960-2017.

- **Countries**: Ratification dates of 1100 multilateral treaties from 1945-2017 acquired from the UN website.
  - Subset by topics: economics, environment, human rights.
  - We estimate the optimal number of edges per year.
  - We set the window at 25 years.
Figure: State Policy, Innovation, and Diffusion (SPID) Dataverse

This Dataverse hosts the data related to the SPID (State Policy Innovation and Diffusion) data. The primary SPID data includes the year of adoption for hundreds of policies that diffused across the American states along with information about the policies. These data are posted in their own data set here. Additional, related resources may also be posted here as separate data sets or studies. The primary SPID data were assembled by the following team under the support of the National Science Foundation (#1558509, #1637095, #1558661, #1558781, and #1558561): Frederick J. Boehmke, Bruce Desmarais, Jeff Harden, and Hanna Wallach (co-PIs) with the support and hard work of Christopher Blythe, Mark Brockway, Scott LaCombe, Fridolin Linder, and Desmond Wallace.

1 to 1 of 1 Result

State Policy Innovation and Diffusion (SPID) Database v1.0
May 31, 2018

Frederick J. Boehmke; Mark Brockway; Bruce Desmarais; Jeffrey J. Harden; Scott LaCombe; Fridolin Linder; Hanna Wallach, 2018, "State Policy Innovation and Diffusion (SPID) Database v1.0", https://doi.org/10.7910/DVN/CVYSR7, Harvard Dataverse, V4, UNF:6:thxlQhN8fn+OohGUN4vView==

The SPID data includes information on the year of adoption for over 700 policies in the American states. For each policy we document the year of first adoption for each state. Adoption dates range from 1691 to 2017 and includes all fifty states. Policies are adopted by anywhere f...
Figure: Examples of Environmental Treaty Cascades
Figure: Number of Edges in Estimated Latent Environmental and Economic Treaty Diffusion Networks

- Number of diffusion edges of environmental treaties
- Number of diffusion edges of economic treaties

Year:
- 1970
- 1980
- 1990
- 2000
- 2010

Number of edges:
- 100
- 150
- 200
- 225
Figure: Examples of Estimated Latent Networks for Environmental and Economic Treaties
Figure: TERGM Results for U.S. States

[Graph showing coefficient estimates for various variables such as Edges, Lagged Network, Transitivity, Reciprocity, Cycling, In-Degree Popularity, Out-Degree Popularity, Difference in Log Population, Log Population, Difference Policy Liberalism, State Policy Liberalism, Difference in Log Income, Log Income, Distance, Time, Time Squared, Time Cubed, along the y-axis with the coefficient estimate on the x-axis.]
Figure: TERGM Results for U.S. States (Subset)
Figure: TERGM Results for UN Treaties
Figure: TERGM Results for UN Treaties - Network Effects
Discussion & Conclusion

1. More fully incorporation network analysis into studies of diffusion valuable.

2. We demonstrate new methods of latent network detection and TERGM estimation.

3. Previous studies of diffusion focus on network and dyads, but rarely on network structures.

4. We find pervasive network effects, though.
## TERGM Results

<table>
<thead>
<tr>
<th></th>
<th>Network and Covariates</th>
<th>Network Only</th>
<th>Covariates Only</th>
</tr>
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<tbody>
<tr>
<td>Edges</td>
<td>−0.67</td>
<td>0.28</td>
<td>−4.62*</td>
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<tr>
<td></td>
<td>[−1.82; 0.57]</td>
<td>[−0.82; 1.58]</td>
<td>[−5.15; −4.12]</td>
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<tr>
<td>Lagged Network</td>
<td>5.15</td>
<td>5.18*</td>
<td>5.19*</td>
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<td></td>
<td>[4.96; 5.36]</td>
<td>[5.00; 5.38]</td>
<td>[5.02; 5.41]</td>
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<td>Transitivity</td>
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<td>0.01</td>
<td></td>
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<tr>
<td></td>
<td>[−0.02; 0.00]</td>
<td>[−0.00; 0.02]</td>
<td></td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.05*</td>
<td>0.10*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.00; 0.11]</td>
<td>[0.05; 0.15]</td>
<td></td>
</tr>
<tr>
<td>Cycling</td>
<td>0.07*</td>
<td>0.05*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.05; 0.08]</td>
<td>[0.04; 0.07]</td>
<td></td>
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<tr>
<td>In-Degree Popularity</td>
<td>−0.82*</td>
<td>−0.82*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[−1.01; −0.68]</td>
<td>[−1.02; −0.66]</td>
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<tr>
<td>Out-Degree Popularity</td>
<td>0.23*</td>
<td>0.20*</td>
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<td></td>
<td>[0.19; 0.27]</td>
<td>[0.17; 0.24]</td>
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<tr>
<td>Diff in Population</td>
<td>−0.08*</td>
<td></td>
<td>−0.07*</td>
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<tr>
<td></td>
<td>[−0.11; −0.05]</td>
<td>[−0.10; −0.04]</td>
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<tr>
<td>Population</td>
<td>0.06*</td>
<td>0.18*</td>
<td></td>
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<tr>
<td></td>
<td>[0.03; 0.08]</td>
<td>[0.16; 0.21]</td>
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<tr>
<td>Diff in Policy Liberalism</td>
<td>−0.16*</td>
<td>−0.16*</td>
<td></td>
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<td></td>
<td>[−0.19; −0.13]</td>
<td>[−0.19; −0.13]</td>
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<tr>
<td>Policy Liberalism</td>
<td>0.07*</td>
<td>0.17*</td>
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<td>Diff in Per Capita Income</td>
<td>−0.72*</td>
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<td>Distance</td>
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<td>[−0.09; −0.04]</td>
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<td>132300</td>
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* Zero lies outside the confidence interval.