

Working with Longitudinal Data

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Basic approaches

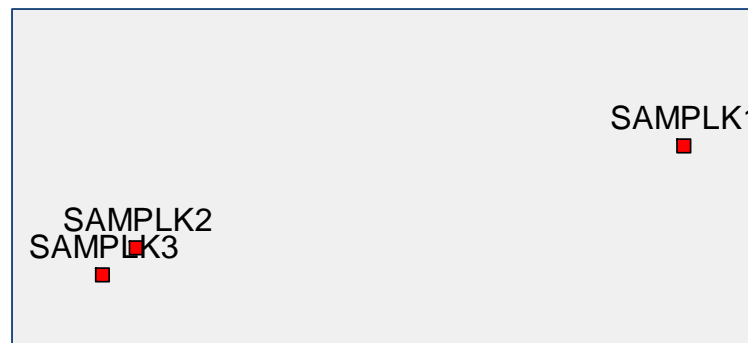
- Multi-relational approach
- Visualization
 - Static representations
 - Animations
 - VISIONE
 - SONIA
- Agent-based statistical models
 - SIENA

Multi-Relational Approach

- Each time point is a slice of a multidimensional actor-by-actor-by-time matrix
 - Just like multiple relations on the same nodes
- Sample datasets
 - SAMPSON dataset includes who likes whom at points in time
 - SAMPLK1 SAMPLK2 SAMPLK3
 - NEWFRAT dataset includes weekly esteem rankings for about 13 weeks

Correlations among matrices (SAMPSON dataset)

	SAMPLK1	SAMPLK2	SAMPLK3
SAMPLK1	1.000	0.645	0.638
SAMPLK2	0.645	1.000	0.768
SAMPLK3	0.638	0.768	1.000



Multidimensional scaling representation

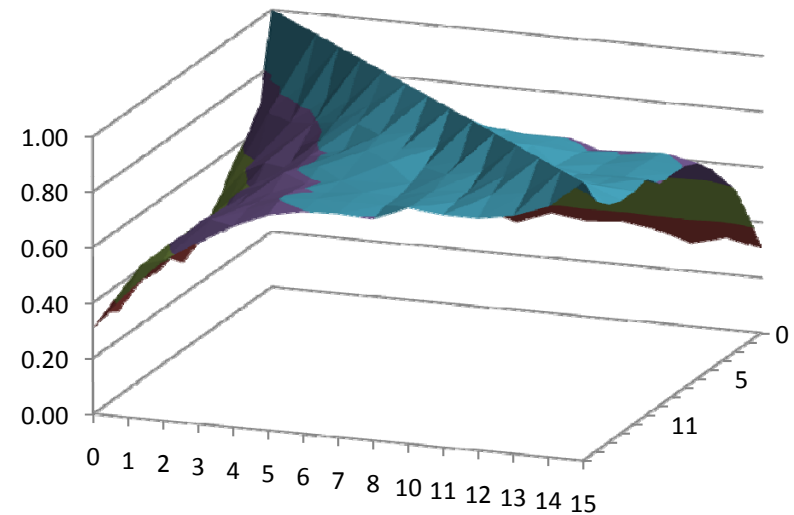
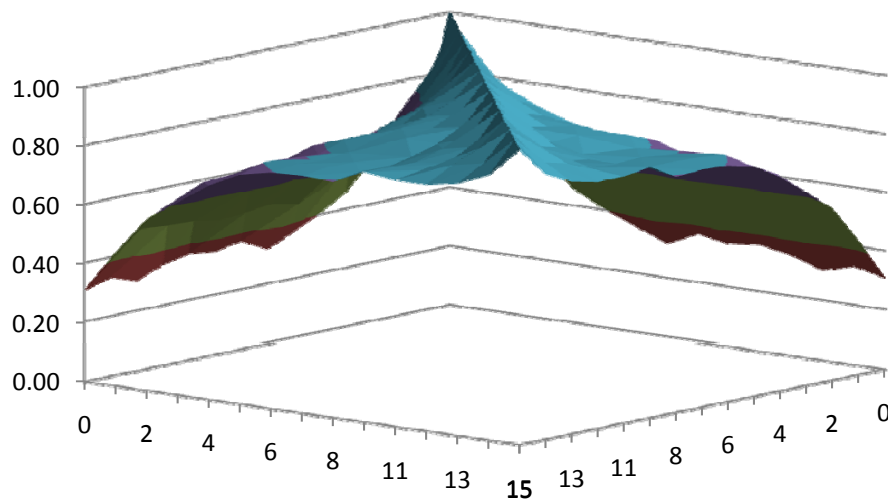
- After T1, social structure changes little

Correlations among matrices (NEWFRAT dataset)

Decline away from T1 →

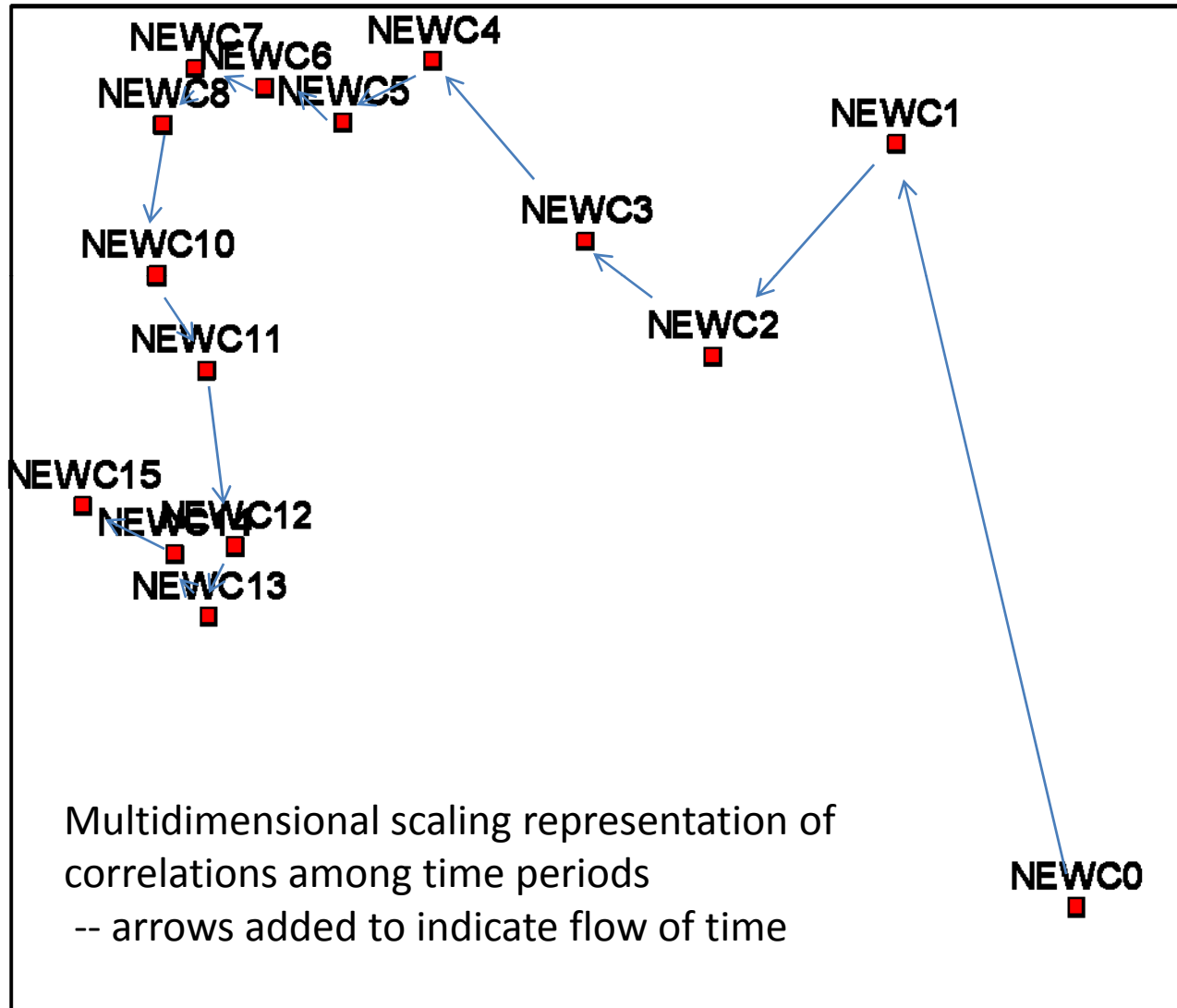
	0	1	2	3	4	5	6	7	8	10	11	12	13	14	15
0	1.00	0.65	0.60	0.55	0.46	0.40	0.36	0.32	0.36	0.35	0.36	0.34	0.30	0.33	0.31
1	0.65	1.00	0.81	0.74	0.60	0.59	0.53	0.49	0.51	0.49	0.49	0.50	0.50	0.51	0.45
2	0.60	0.81	1.00	0.85	0.75	0.69	0.67	0.60	0.63	0.61	0.61	0.62	0.61	0.62	0.58
3	0.55	0.74	0.85	1.00	0.84	0.79	0.74	0.69	0.70	0.70	0.70	0.69	0.68	0.70	0.65
4	0.46	0.60	0.75	0.84	1.00	0.88	0.84	0.81	0.78	0.77	0.79	0.74	0.75	0.75	0.72
5	0.40	0.59	0.69	0.79	0.88	1.00	0.91	0.88	0.82	0.82	0.82	0.79	0.80	0.80	0.78
6	0.36	0.53	0.67	0.74	0.84	0.91	1.00	0.92	0.88	0.86	0.84	0.81	0.80	0.81	0.80
7	0.32	0.49	0.60	0.69	0.81	0.88	0.92	1.00	0.90	0.87	0.86	0.82	0.81	0.82	0.80
8	0.36	0.51	0.63	0.70	0.78	0.82	0.88	0.90	1.00	0.89	0.85	0.83	0.81	0.81	0.80
10	0.35	0.49	0.61	0.70	0.77	0.82	0.86	0.87	0.89	1.00	0.89	0.87	0.84	0.84	0.85
11	0.36	0.49	0.61	0.70	0.79	0.82	0.84	0.86	0.85	0.89	1.00	0.89	0.86	0.85	0.84
12	0.34	0.50	0.62	0.69	0.74	0.79	0.81	0.82	0.83	0.87	0.89	1.00	0.92	0.88	0.83
13	0.30	0.50	0.61	0.68	0.75	0.80	0.80	0.81	0.81	0.84	0.86	0.92	1.00	0.91	0.85
14	0.33	0.51	0.62	0.70	0.75	0.80	0.81	0.82	0.81	0.84	0.85	0.88	0.91	1.00	0.90
15	0.31	0.45	0.58	0.65	0.72	0.78	0.80	0.80	0.80	0.85	0.84	0.83	0.85	0.90	1.00

Correlations among matrices (NEWFRAT dataset)

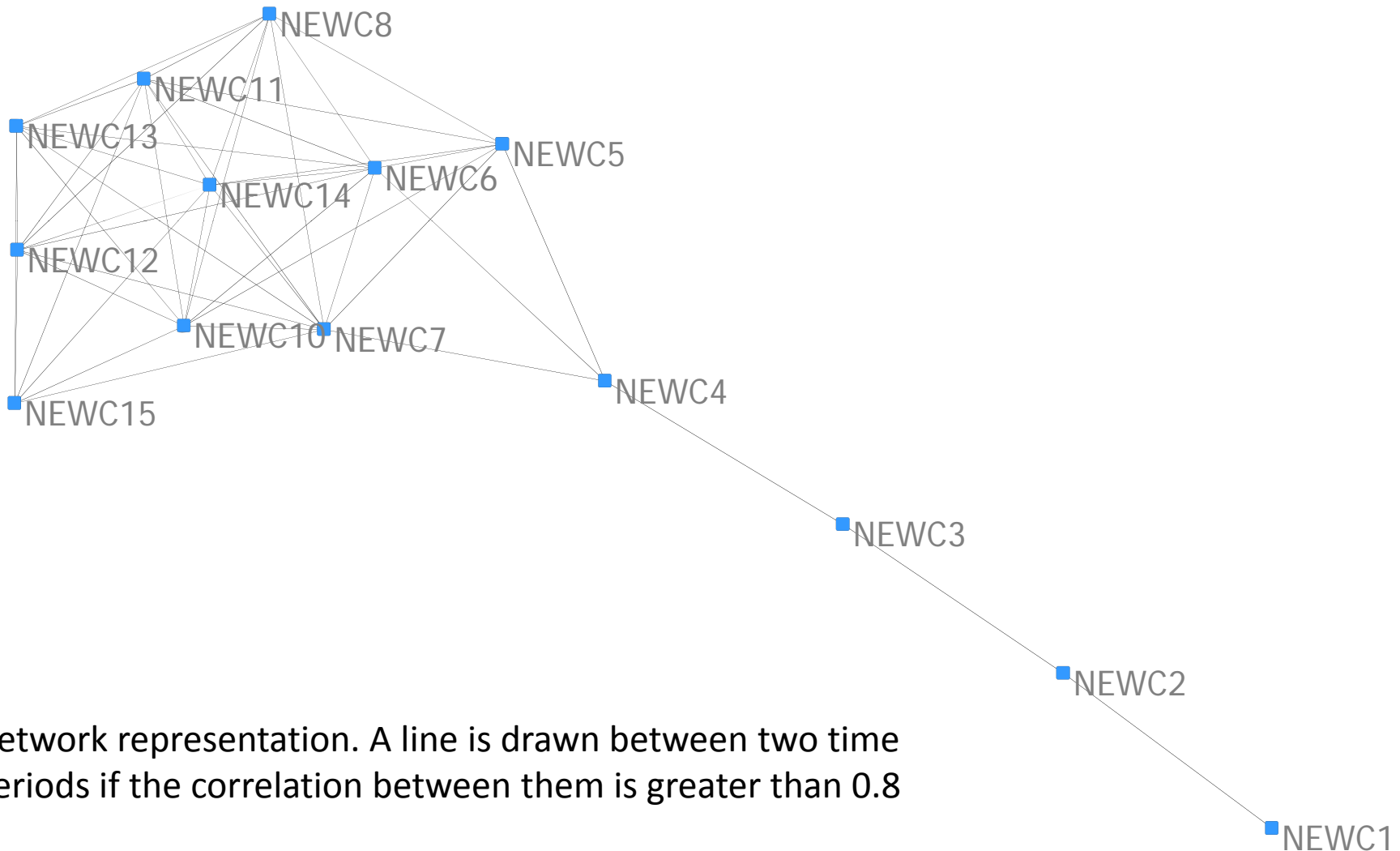


- Correlations drop off as time difference increases
- Correlations drop faster at the early time points

Correlations among matrices (NEWFRAT dataset)

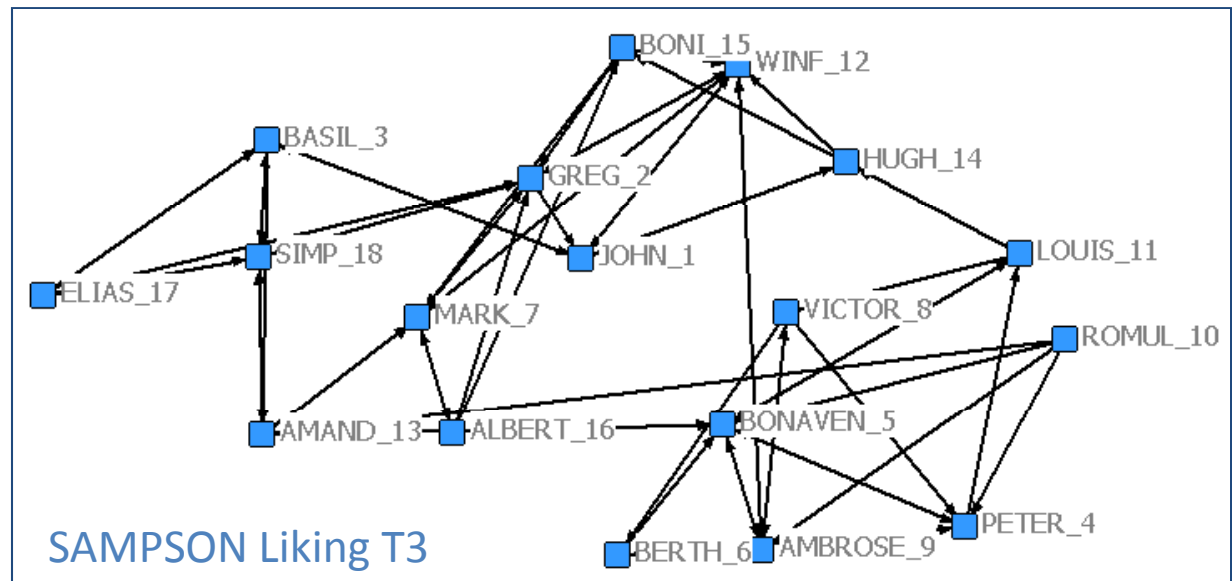
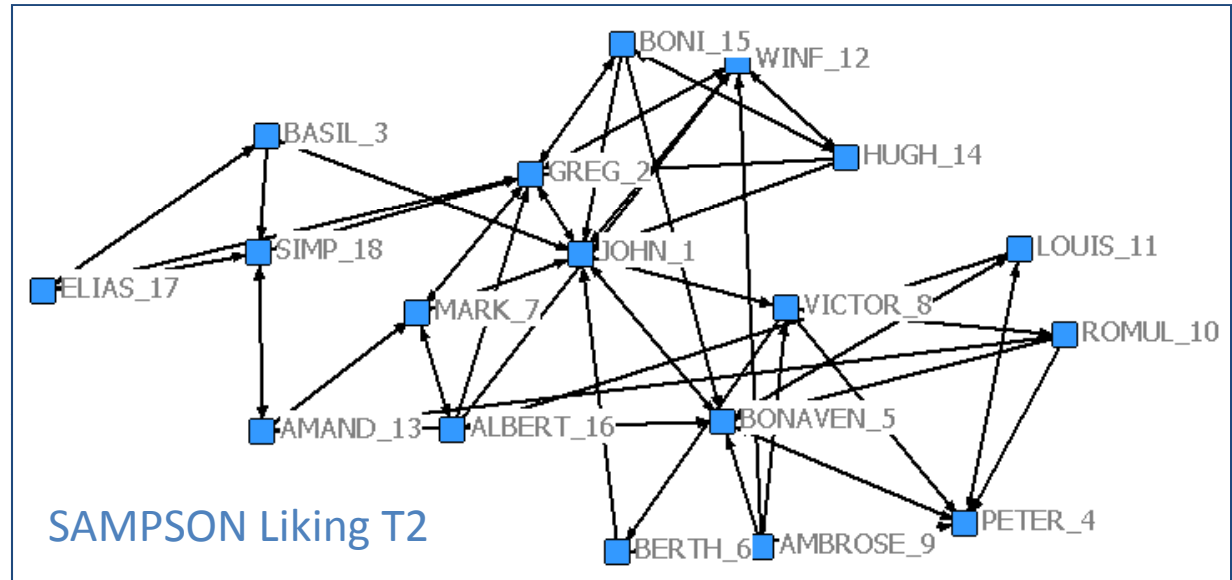


Correlations among matrices (NEWFRAT dataset)

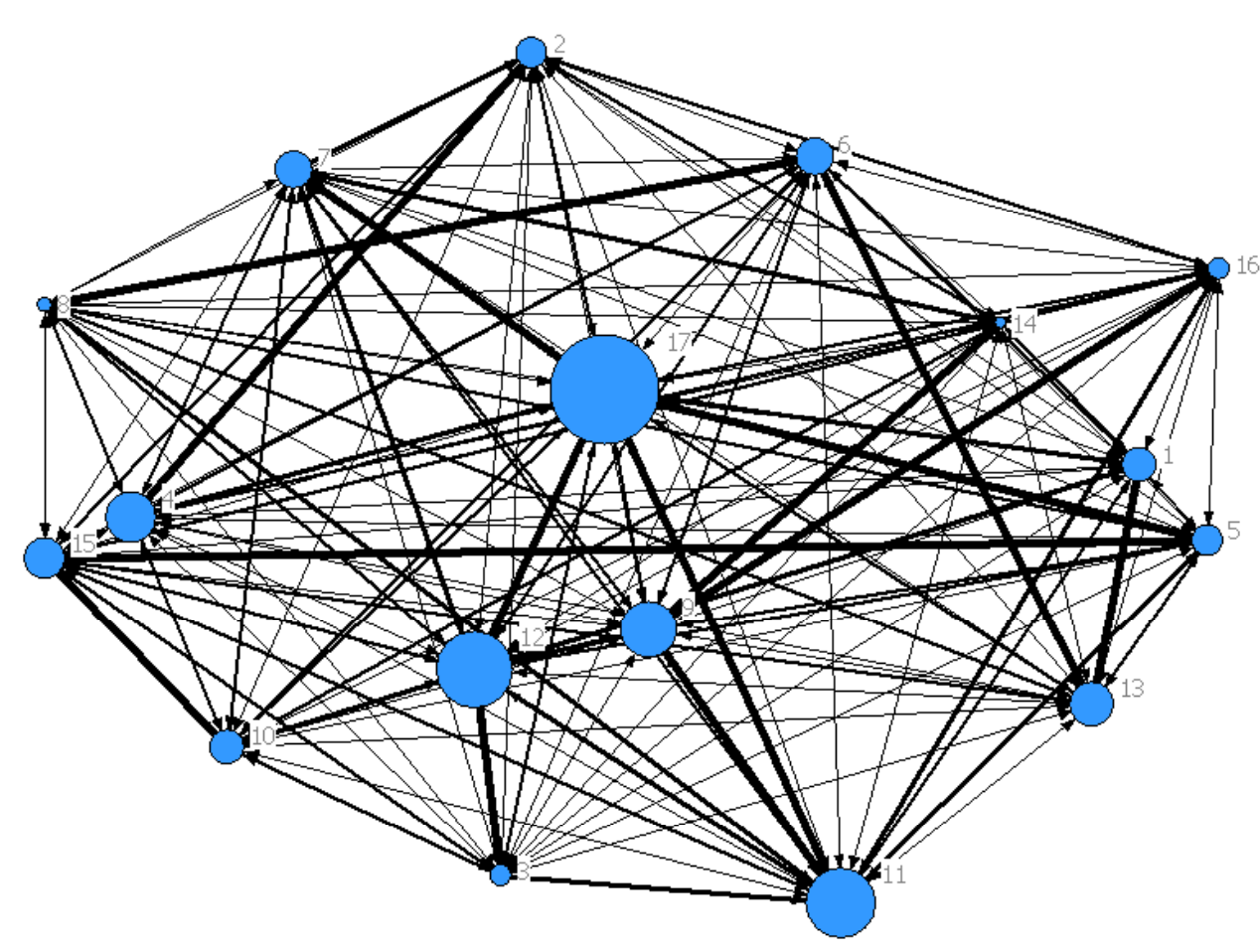


Visualizing tie-level changes

- Side-by-side display
 - Static representation
 - Nodes don't change positions
- Requires small networks, few time periods



Newcomb data over time

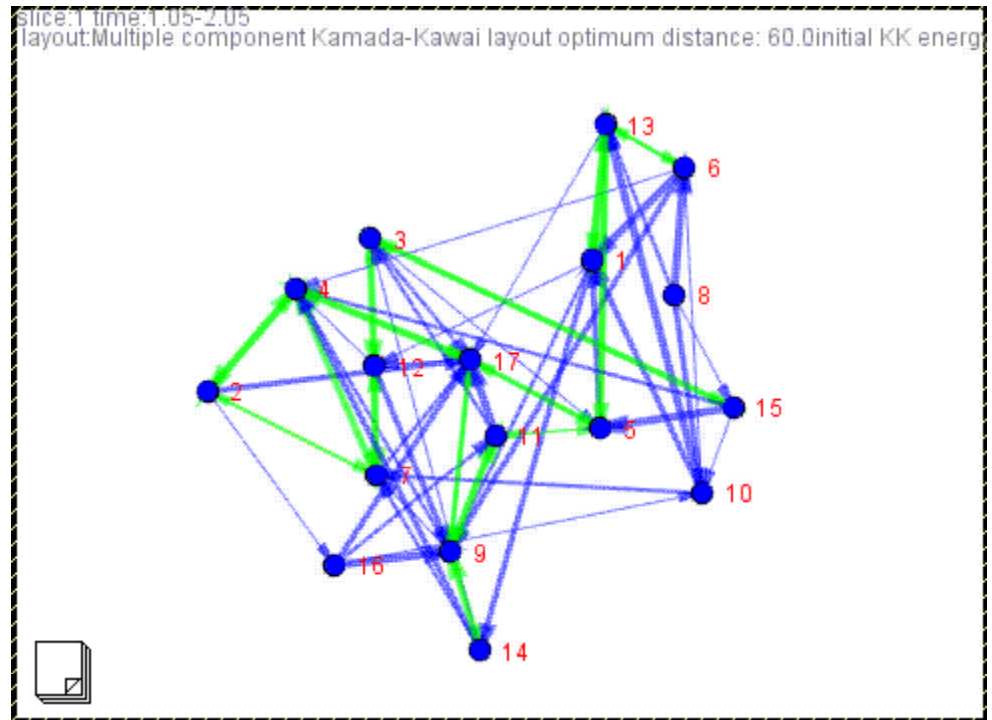


- Changes in tie strength (and centrality) over time
- Node positions fixed

(animation)

Newcomb data over time

- Node positions change over time
- Issues with maintaining the meaning of the motion/position link
 - Brownian motion of the spring embedder
 - But see visone for algorithmic improvement



Anthony Dekker. 200?. Conceptual Distance in Social Network Analysis. Journal of Social Structure. (Vol. 6, No. 3)

uses of motion as design element

1968

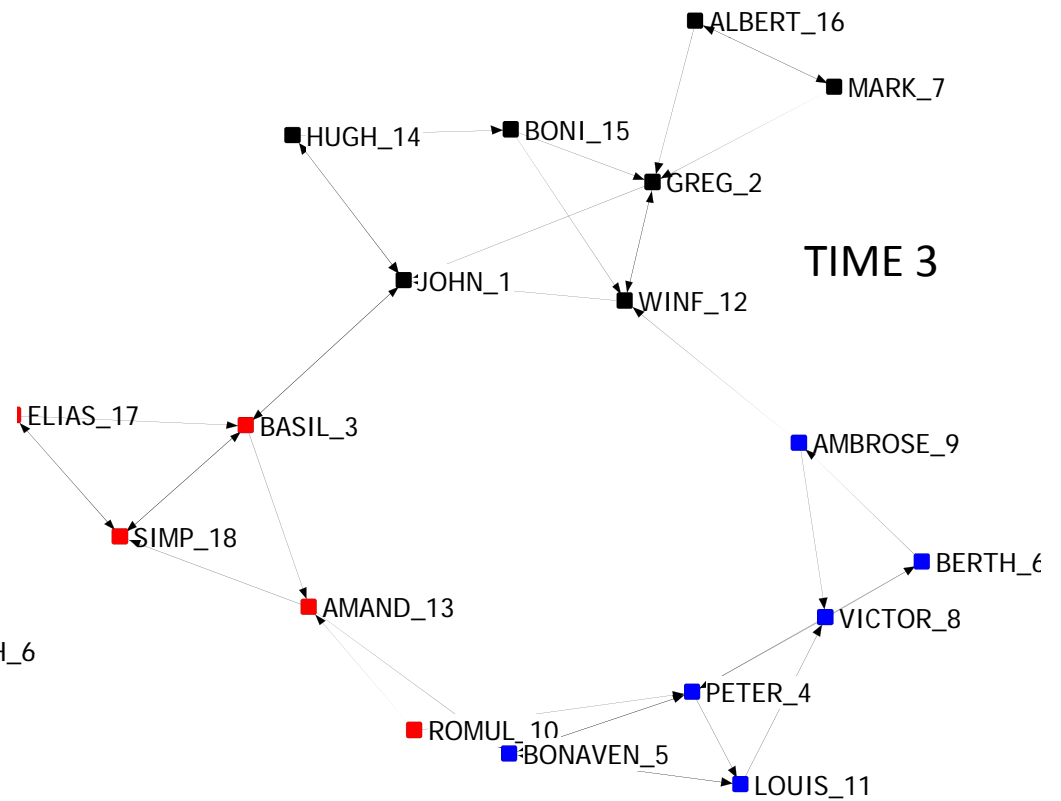
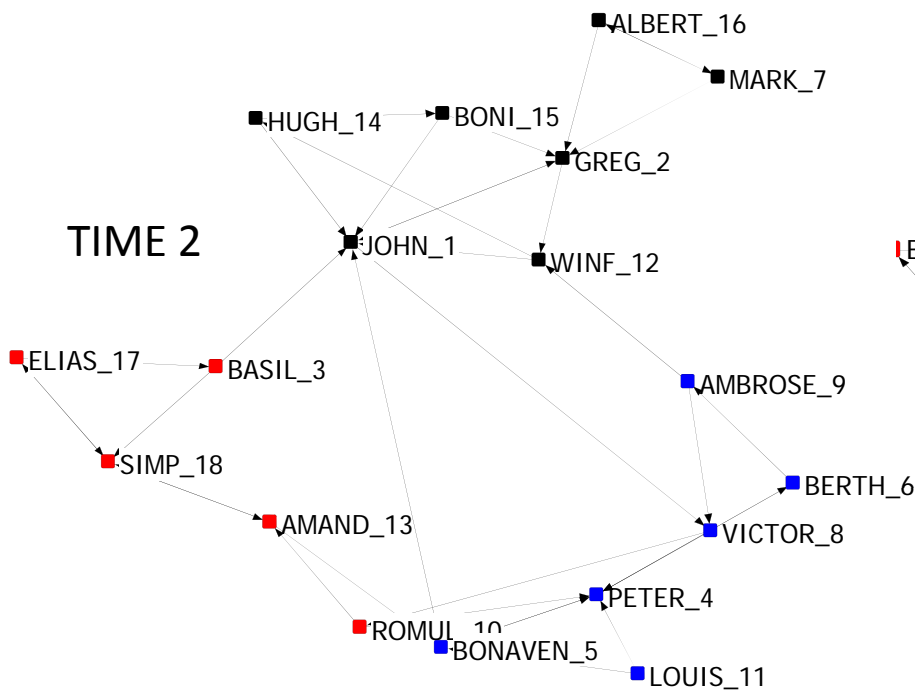
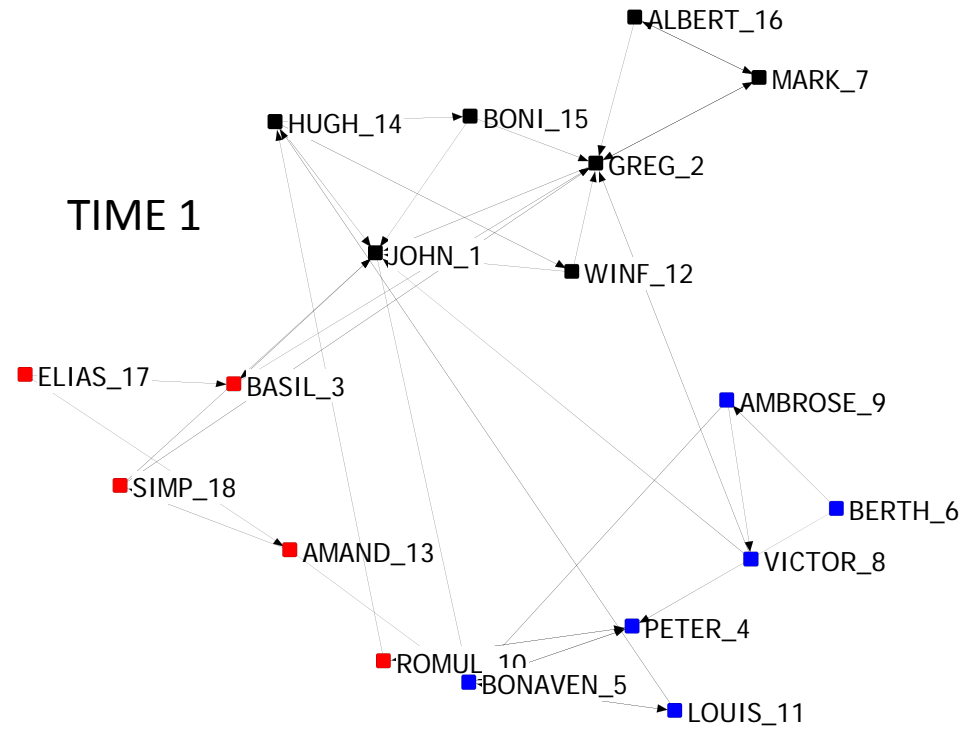
Case III

- Nodes maintain fixed positions, ties appear and disappear
 - Ignores changes in centrality etc.
 - Traces help maintain memory but this is still issue

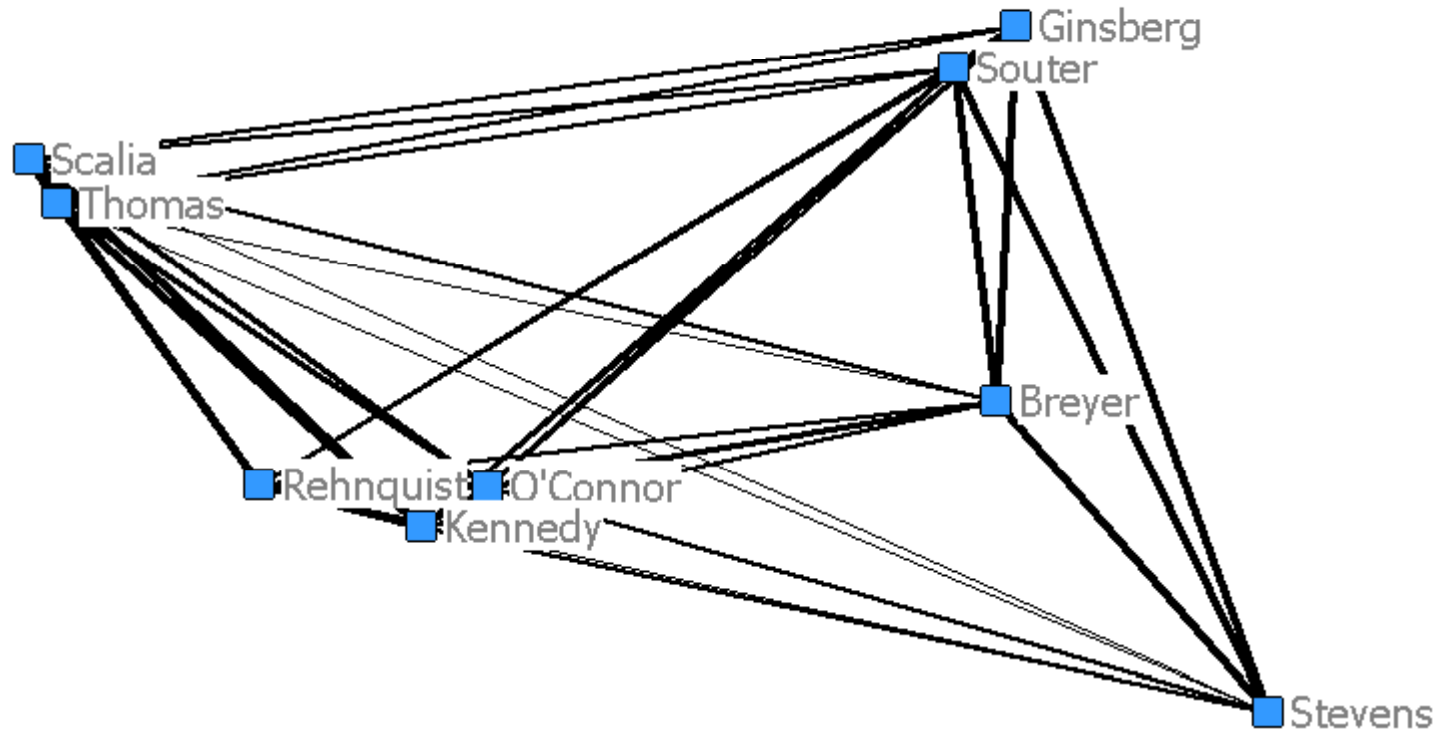


Moody, James, Daniel A. McFarland and Skye Bender-DeMoll. 2005. "[Dynamic Network Visualization: Methods for Meaning with Longitudinal Network Movies](#)" *American Journal of Sociology* 110:1206-1241.

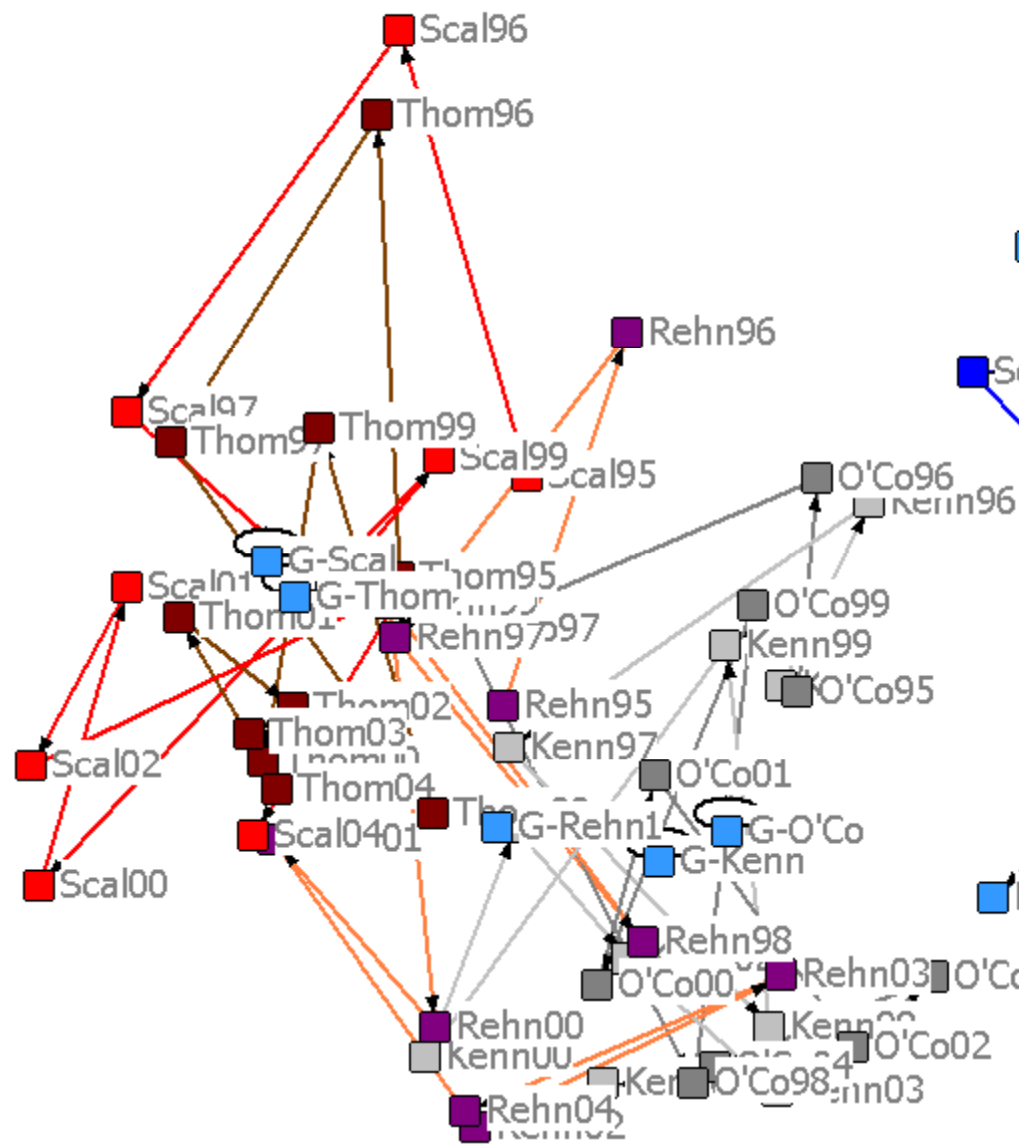
simpler side by side displays still have advantage of comparability



Supreme Court Data

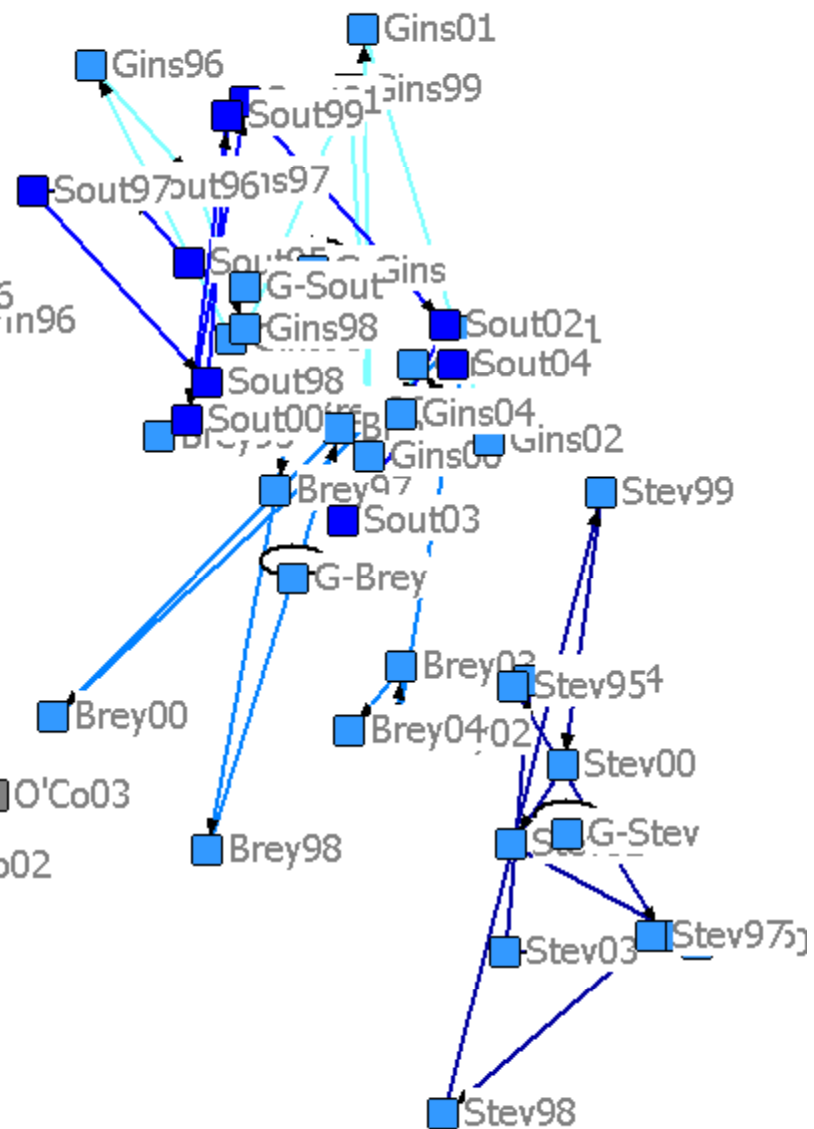


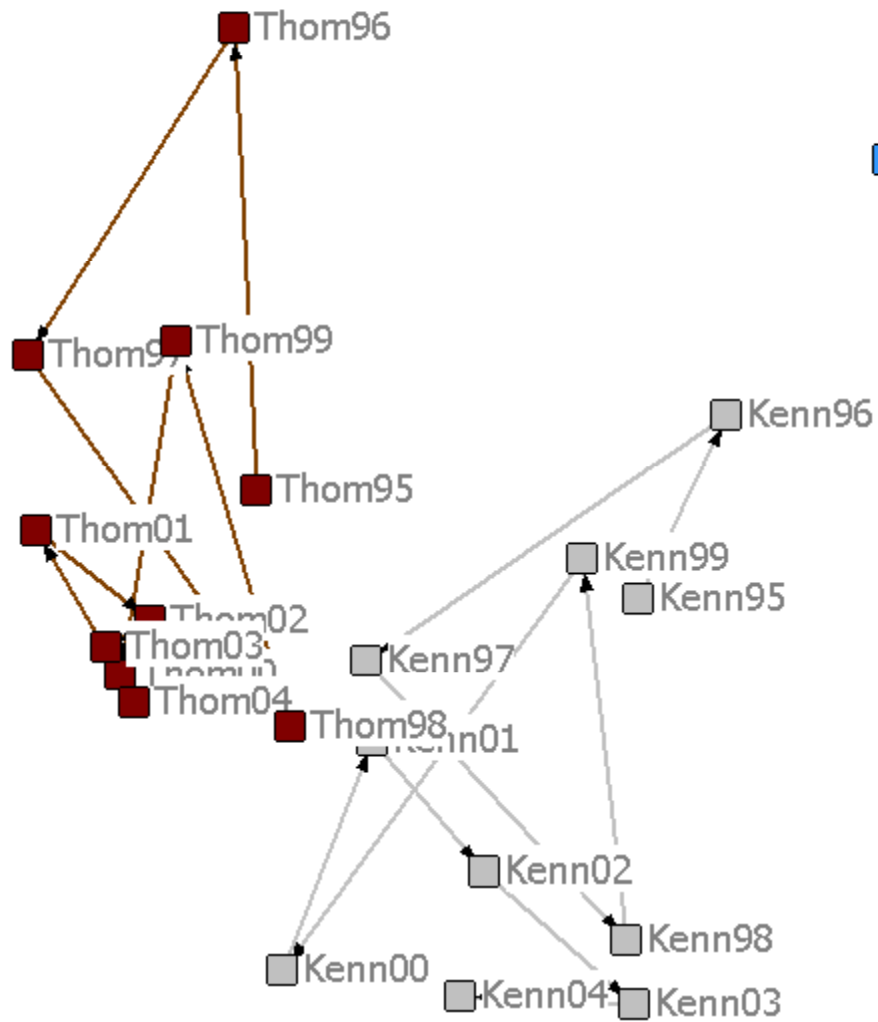
How often judges were together on the majority across all 10 years



Stacked Correspondence analysis

Supreme Court Data
-- all years, all judges





Stacked Correspondence analysis

Supreme Court Data
-- all years, selected judges

