Applied Physics Laboratory
University of Washington

FINAL TECHNICAL REPORT

ONR Grant N0014-13-1-0381
Integrated Modeling of Themes, Targeting Claims and Networks in Insurgent Rhetoric

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Period of Performance: March 1, 2013 – February 28, 2016

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Appendices (in separate volume)

1 Scope

This report describes research conducted by the Applied Physics Laboratory of the University of Washington (APL-UW) for the Office of Naval Research (ONR) under grant N00014-13-1-0381. The research performed under this grant involved two main objectives. One was the development of new capabilities for leadership network modeling and analysis building upon our model of nonlinear social influence dynamics. The second objective was the development of analysis methods and models for insurgent networks. The research was conducted by APL-UW personnel Dr. Michael Gabbay (PI) and postdoctoral fellow Dr. Zane Kelly. We note that the grant was only partially funded, receiving $321,750 out of an originally-planned amount of $826,000.

2 Accomplishments

The following are significant accomplishments of our effort:

1) Developed PORTEND prototype software package for leadership network modeling and analysis.
2) Supported transition of methodology and software to STRATCOM. PORTEND has recently been applied in-house by STRATCOM to two case studies.
3) Developed method of assessing the importance of ideology as a driver of network structure based on community structure.
4) Demonstrated the importance of ideology in tie formation processes in Iraqi insurgent cooperative networks using the community structure algorithm and exponential random graph models (ERGMs).
5) Developed an initial extension of the nonlinear social influence model used in PORTEND to a two-dimensional issue space. Model formulation and application to Iran presented to STRATCOM.

3 Summary of Research

In this section, we summarize key elements of this research effort. Reference numbers refer to documents listed in Section 5.1.

3.1 Leadership Network Modeling and Analysis

We developed a Matlab-based prototype software package called PORTEND (Political Outcomes Research Tool for Elite Network Dynamics). PORTEND integrates quantitative techniques from nonlinear systems theory and network science to aid the analysis of policy and factional outcomes with respect to the internal dynamics of a system of political actors. The political actors may be individual leaders or organizations within a government or movement. The outcomes of concern may be policy decisions, winning and losing factions, the positions of individuals, or the potential for issues to cause dissension or factional realignment. Political actors are represented mathematically with respect to their preferences on one or more issues, the saliences of those issues, the network of inter-actor influence, and actor power and susceptibility to influence. The data from which these quantities are calculated is obtained from surveys given to expert analysts. PORTEND imports these surveys and aggregates them to form a composite analyst if desired. It then allows for structural analysis regarding issues and the inter-actor network and for the simulation of social influence and group decision making outcomes. The analyses can be performed for the composite analyst or separately for the individual analysts. An overview of the methodology is shown in Figure 1.

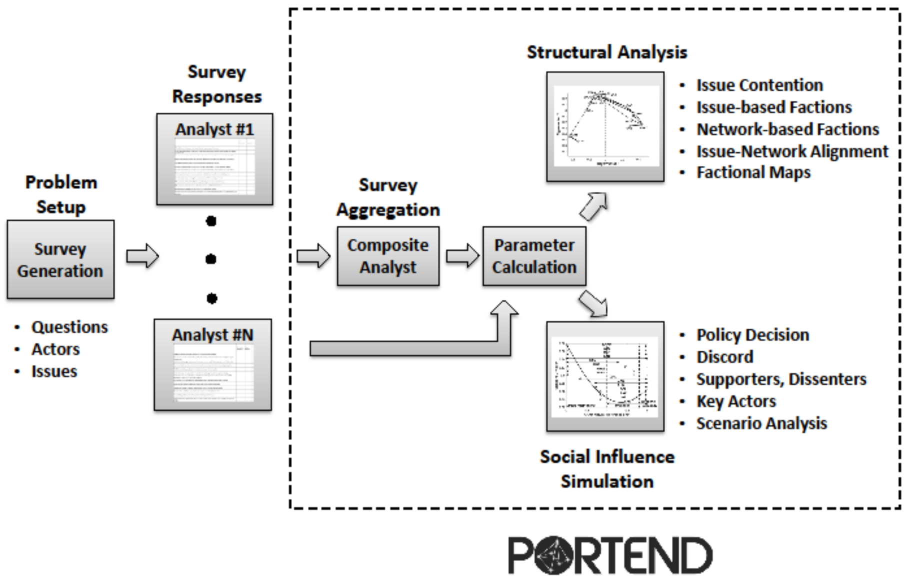

Figure 1. Methodology overview.

The PORTEND User Guide can be found in Appendix 1. Under ONR/DTRA grant HDTRA1-10-1-0075, the PORTEND methodology was applied to Iranian elites with a focus on nuclear decision making [4].

3.2 Community Structure and Ideology

We developed a technique for analyzing and visualizing the relationship between structure in the network of ties between actors and actor ideologies or policy positions. Network science has developed many algorithms for detecting community structure in networks. Intuitively, the goal is to find subgroups of nodes that have more links among them than they do with other subgroups. While these algorithms typically only employ the network itself and not node attributes, the communities they reveal often consist of clusters of nodes with similar attributes reflecting the prevalence of homophily within social networks. Consequently, the alignment of community structure within a network with a particular node attribute, such as ideology or issue positions, provides evidence that homophily is important in driving that structure.

The algorithm we employ was designed to divide a network into two communities so that the network "modularity" is maximized (M. E. J. Newman, Physical Review E 74 (3), 036104 2006). The modularity expresses the extent to which a putative division of the network into two communities exhibits a level of intra-community linking exceeding the level expected if the division were, in fact, arbitrary with no correspondence to behaviorally meaningful subgroups. If a given pair of nodes is assigned to the same community, their dyad's contribution to the modularity is proportional to the difference between the observed tie strength and that which would be expected if their interactions were solely due to chance. The algorithm assigns nodes into communities on the basis of the first eigenvector of the modularity matrix (loosely speaking, distinct eigenvectors form independent directions which do not mix with each other under operation of the matrix). Statistical tests of homophily between a node variable and network structure can then be conducted by: (1) correlating the first eigenvector with the node variable; or (2) assessing the extent to which the algorithm's division into two communities matches that produced by the binarized node variable.

Formally, we consider a weighted, symmetric network with N nodes and adjacency matrix components A_{ij}. The degree of node i is the sum of its incident tie strengths, $k_i = \sum_{j=1}^{N} A_{ij}$ and total degree given by $\sum_{i=1}^{N} k_i = 2m$. These network quantities are used to define the components of the modularity matrix **B**,

$$B_{ij} = A_{ij} - \frac{k_i k_j}{2m},$$

which is the difference between the observed tie strength and that which would be expected from a null model in which ties are formed in proportion to the product of node degrees. The modularity for a candidate partition of the nodes into two communities is the sum of a subset of the modularity matrix components: a given B_{ij} will contribute to the modularity if i and j are assigned to the same community. The optimal partition is the one which maximizes the modularity.

Newman (2006) presents an approximate but efficient solution to the modularity optimization problem using the spectrum of the modularity matrix defined via $\mathbf{B}\mathbf{u}_\nu = \lambda_\nu \mathbf{u}_\nu$ where λ_ν is the eigenvalue corresponding to eigenvector $\mathbf{u}_\nu$ with eigenvectors indexed in order of decreasing eigenvalue (the eigenvalues are real since **B** is real and symmetric). Each eigenvector $\mathbf{u}_\nu$ is N-dimensional with a component for each node written as $u_i^{(\nu)}$. The leading eigenvector $\mathbf{u}_1$ is then used to determine the separation of nodes into two communities C_1 and C_2 according to whether its component for a given node i is positive or negative respectively:

$$i \in \begin{cases} C_1 & \text{if} \quad u_i^{(1)} \geq 0 \\ C_2 & \text{if} \quad u_i^{(1)} < 0. \end{cases}$$

If the leading eigenvalue is zero, then all the $u_i^{(1)}$ are identical and all nodes are assigned to just one community.

The larger the magnitude of a node's component in the first eigenvector, $|u_i^{(1)}|$, the more strongly it can be associated with its assigned community. Consequently, if a scalar variable x associated with each node is thought to be important in driving network structure, the existence of a statistically significant correlation between the components of the first eigenvector $\mathbf{u}_1$ and the node variable values x_i would provide support for the hypothesized relationship. More generally, the assortativity, a measure of homophily in the network with respect to a scalar variable x, can be expanded as a sum of the modularity matrix eigenvalues where the weight associated with each λ_ν is proportional to the square of the inner product of the vector formed by the x_i and the associated eigenvector $\mathbf{u}_\nu$, $(\sum_{i=1}^{N} u_i^{(\nu)} x_i)^2$. Homophily therefore can be manifested by significant correlations of the variable with a highly ranked eigenvector (of positive eigenvalue), not just the leading one. However, as the first eigenvector represents the dominant community structure, significant correlation with it indicates a particularly strong association between the variable and network tie formation.

The application of the algorithm to Iraqi insurgents is shown in Figure 2. The data is obtained from insurgent rhetoric [2]. The dashed line partitions groups having opposite signs on the first eigenvector into two communities as described above. Firstly, we observe very good agreement of the network-based communities with a binary ideology coding into jihadist (squares) and nationalist (circles) groups. A continuous measure of ideology, the "conflict frame" which uses key words and phrases in group rhetoric, can be correlated with the group coordinates along the first eigenvector to test for homophily. The value obtained is 0.69 which is statistically significant at the p<.01 level indicating that ideological proximity is an important driver of network structure. We have recently applied this technique to Syrian militant groups and have obtained a similar result.

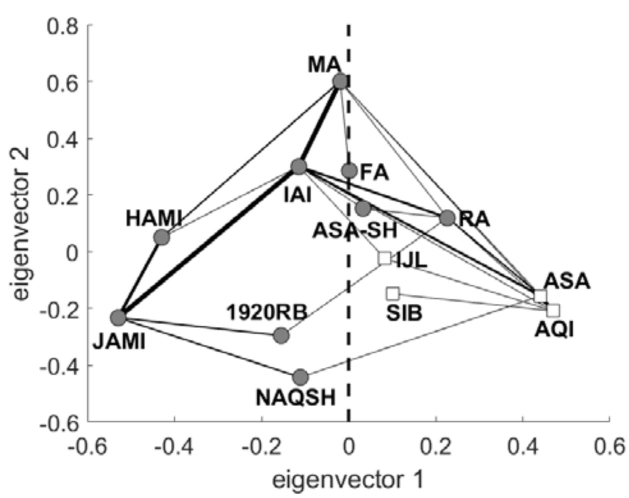

Figure 2. Community structure in network of joint operations of Iraqi insurgent groups during the period August 2007 – July 2009. Groups coded as having jihadist ideologies are shown as open squares, nationalists as solid circles.

The algorithm has been incorporated within PORTEND and was used in the Iran analysis [4] as shown in Figure 3. Six of seven issues correlated significantly with the first eigenvector (Factional Dimension 1 in the figure) demonstrating the presence of strong ideological homophily in the network. However, one issue aligned with the second eigenvector suggesting the potential for factional realignment into a distinct community structure should that issue become more salient.

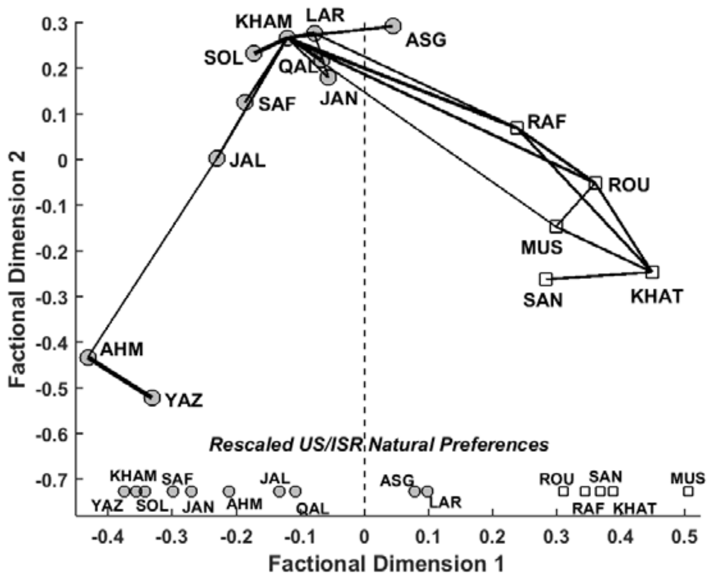

Figure 3. Community structure in the Iranian leadership network. Dashed line partitions network into two communities which agree very well with ideology-based coding into conservatives (solid circles) and reformers (open squares). Link thickness between actors is proportional to relationship strength (weak links have been thresholded). Points at bottom of plots are actor issue positions regarding relations with the US and Israel (rescaled to fit inside the horizontal axis).

3.3 ERGM Analysis of Iraqi Insurgent Networks

We applied exponential random graph models (ERGMs), a statistical technique for assessing the importance of candidate tie formation processes in social networks, to Iraqi insurgent networks. Given that the observed network is only one possible permutation of ties among nodes, the ERGM method can be used to relate tie formation processes involving both topological and node variable mechanisms to the likelihood of observing a given network. It does so by estimating a parameter associated with each process via a Markov Chain Monte Carlo maximum likelihood which simulates many networks. Significance levels can then be associated with the parameters.

The ERGM analysis was applied to both tactical and leadership level cooperative networks constructed from (claimed) joint operations and joint statements respectively. We used ERGMs to investigate the relationship of network structure to ideology and targeting policy – a measure of the legitimacy (within the movement) of a group's portfolio of its claimed target classes. Table 1 shows the ERGM parameter estimates for networks during three periods of the Iraqi insurgency. Having a common jihadist or nationalist ideology was found to enhance the probability of tie formation and groups with proximate targeting policies were more likely to form ties than groups with more distant ones. The results are described in Ref. [5].

Tactical Network - Joint Operations

	2003-05	2005-07	2007-09
Edges	-2.833**	-1.590***	-1.079**
	(1.099)	(0.481)	(0.530)
Ideology	0.000	1.362***	1.036**
	(0.867)	(0.501)	(0.493)
Targeting policy	2.610**	-0.985*	-1.000*
	(1.133)	(0.555)	(0.595)
Leadership Network - Joint Statements			
Edges	-1.059*	-2.343***	-2.163***
	(0.526)	(0.646)	(0.431)
Ideology	-0.583	3.249***	2.178***
	(0.831)	(0.765)	(0.551)
Targeting policy	1.222	-1.716**	-1.710***
	(0.876)	(0.719)	(0.640)
Groups	9	18	16

*p < .1; **p < .05; ***p < .01

Table 1. ERGM parameter estimates for Iraqi insurgent tactical and leadership networks.

3.4 Insurgent Network-Targeting Coevolution Model

We developed an initial model for the coevolution of militant networks and their force allocation policies. The following observations based on our analysis of the Iraq conflict were used to guide formulation of the model: (1) homophily in group ideologies, conflict frames, and targeting policy was observed to be important in tie formation; (2) more powerful groups tend to have higher network degrees and hence guide the structure of the network and ultimately alliance formation; (3) the history of cooperation is important so that dyads which have cooperated in the recent past are more likely to do so in the future; and (4) groups compete to steer the nature of the conflict, particularly the axis of violence – an example of such competition occurred in the Iraq conflict in which Al Qaida in Iraq (AQI) sought to foment sectarian violence against Shiites whereas nationalist Sunni groups sought to maintain the focus on US forces.

In the model, network ties represent the level of military cooperation between dyads and the “force policy vector” represents how individual groups allocate their forces against other conflict parties, e.g., rival ethnic groups and occupying forces. Each militant group has a "natural preference" with respect to its preferred allocation of force against the conflict parties given its ideology and goals. In turn, the level of force directed against militant groups from each of these conflict parties defines the "threat vector." The network evolution equation evolves the level of cooperation between militant dyads in response to the threat vector, individual group and aggregate militant force policy vectors, and changes in the network itself. The force policy evolution equation holds that a group's force policy evolves in response to the threat vector, the policies of their partners, and how far the current aggregate force policy vector is from the group's natural preference. A group can seek to cooperate with another in order to meet the threat vector or to steer the aggregate policy vector toward its natural preference – this allows groups to compete over what the axis of violence should be.

Formally, we write the model as a system of coupled ordinary differential equations:

$$\frac{d\rho_{ij}}{dt} = (\rho_{ij}\rho_{ji})^{1/2}(\beta s_i - \sum_{k=1}^{N}\rho_{ik})(\beta s_j - \sum_{k=1}^{N}\rho_{jk})\left\{\theta v \cdot x_j + c_i(\mu_i - f)\cdot(x_j - f) - \alpha_0 - \alpha_i \left\|x_j - x_i\right\|^2\right\} \qquad (1)$$

$$\frac{dx_i}{dt} = \omega\left\{-\gamma_i(x_i - \mu_i) + \sum_{j=1}^{N}\rho_{ji}(x_j - x_i) + \frac{\theta}{\theta_0}(v - x_i)\right\}. \qquad (2)$$

The dynamical variables are: the cooperation rate ρ_{ij}, the number of units per time that group *i* allots to working cooperatively with *j* (note that it is, in general, asymmetric, $\rho_{ij} \neq \rho_{ji}$); and the force policy vector x_i, the actual fraction of group *i*'s military power allocated against each of the conflict parties. The parameters, i.e., those quantities which are taken as fixed, are as follows: the number of militant groups *N*; the size s_i, the number of tactical units in each group; the natural preference μ_i, the group's ideal force policy vector as determined by its ideology and strategy; the commitment γ_i which scales the extent to which the pull of the group's natural preference inhibits policy change; the aggregate force policy vector of all the groups, *f*; the threat vector *v*, the share of the total threat posed by each of the conflict parties against the militants; the total threat level θ; the nominal threat level θ_0; the policy gap scale factor, c_i, which represents how strongly each group seeks to steer the aggregate policy toward its natural preference; the fixed cooperation cost α_0 of operating with another group; the policy distance-dependent cooperation cost factor α_i; the operational tempo β, the number of operations per unit time; and the policy change rate scale ω.

The magnitude of the aggregate force policy vector is greater if militants cooperate with each other than if they do not. In the model, this is implemented using the physics notion of coherent superposition (such as occurs in lasers but not in ordinary white light): cooperation causes the units from different groups engaged in joint action to add coherently whereas independent action results in incoherent addition.

Equation (1) evolves the network ties. The terms inside the braces reflect the benefits and costs as group *i* increases its cooperation with group *j*: the first term states that the more group *j*'s allocation of force meets the incoming threat vector, the more benefit there is to cooperating with it; the second term models the extent to which group *j* can help steer the policy vector toward *i*'s natural preference; the third term represents the fixed cost of cooperating with any other group due to, for instance, coordination and planning costs; and the fourth term expresses the greater cost of operating with a group whose policy is distant from one's own (an example is the reputational damage caused to the Free Syrian Army by its cooperation with extremist jihadist groups which made its Western backers more hesitant to provide support). The prefactor immediately before the braces accounts for the fact that groups only have so many units with which they can engage in joint operations, the larger groups having more capacity. The first prefactor expresses the ability of a dyad with a high present degree of cooperation to step up their cooperation rate, all other things being equal, thereby accounting for past cooperation. Equation (1) is nonlinear in both cooperation rates and policy vectors.

One way the model can be employed is to note how the behavior changes as parameter values are changed. This can identify qualitatively distinct regimes of behavior due to bifurcations as are often present in nonlinear systems. Figure 4 shows the changes in the simulated equilibrium network structure as the threat level changes. There are two tiers of militant group sizes: a top tier consisting of three large groups (squares), each of which dominates a given region of the policy axis – left (1), center (2), and right (3); and a second tier of small groups (circles) uniformly distributed across the policy axis. This is roughly analogous to the situation in Iraq prior to the Sunni Awakening in which three different groups – AQI, the Islamic Army in Iraq (IAI), and the 1920 Revolution Brigades (1920RB) – dominated each part of the targeting policy and conflict frame spectrum. Militants are taken to face an equal threat level from two different conflict parties, such as Sunni insurgents facing both the US and Shiites in Iraq. At a low threat level (Figure 4 (a)), a heavily factionalized situation prevails: there is no cooperation among the top tier groups, each operating with its own set of like-minded second tier partners. However, past a certain critical threat level, a bifurcation occurs in which the top tier groups cooperate substantially with each other as can be seen by the thick lines that connect group 2 with groups 1 and 3 in Figure 4(b); the middle top-tier group acts as a bridge between the different wings of the insurgency akin to the role played by the IAI in Iraq. Further increasing the threat level produces a clique among the three top-tier groups in which they cooperate at high rates with each other as seen in Figure 4(c).

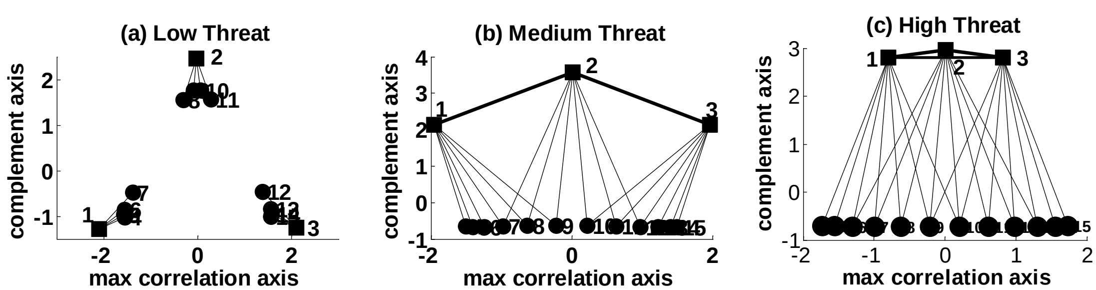

Figure 4. Simulated networks using two tiers of militant group sizes. (a) Low threat level, θ/θ_0 = 2.1; (b) Intermediate threat level, θ/θ_0 = 2.5; (c) High threat level, θ/θ_0 = 3. Squares indicate top tier groups. Weak ties have been thresholded.

In the language of network science, Figure 4(c) corresponds to a core-periphery network as is commonly exhibited by social networks. Further increasing the threat level would bring the policies of all groups closer together, thereby approaching a giant component in which the nodes have all homogenized so that they share the same attribute values; such a single homogeneous cluster is one of two possible equilibria in standard network coevolution models which incorporate only homophily and attractive social influence. The heavily factionalized state of Figure 4(a) corresponds to the second possible equilibrium consisting of disconnected islands, which are homogeneous within but differ from each other. However, Figure 4(b) shows an intermediate equilibrium that is inaccessible to standard coevolution models, one in which there are significant ties present between top-tier nodes, yet those nodes retain substantial force policy differences.

4 Transition

This effort, particularly the leadership network modeling and analysis element, involved close collaboration with STRATCOM to facilitate transition. The components of the PORTEND methodology were presented in detail and STRATCOM personnel provided substantial guidance throughout its development. STRATCOM personnel received training on the construction of the subject matter expert survey which provides the data for PORTEND and have successfully developed these surveys in-house which have been completed by government and independent analysts. The software was delivered to STRATCOM in November 2014 and the PI gave a two-day training course on its basis and use. PORTEND has recently been applied to leadership networks in two countries in which STRATCOM personnel and the PI jointly conducted the analysis and presented the results to government analysts.

5 Publications and Presentations

5.1 Publications

1. Gabbay, M., "Modeling Decision-Making Outcomes in Political Elite Networks," in K. Glass et al (Eds.): *Complex Sciences*, LNICST 126, 95-110, 2013.
2. Gabbay, M., "Data Processing for Applications of Dynamics-Based Models to Forecasting," in Egeth, J.E., Klein, G.L., and Schmorrow, D. (Eds.), *Sociocultural Behavior Sensemaking: State of the Art in Understanding the Operational Environment*, McLean, VA: The MITRE Corporation, 2014. (**Appendix 2**)
3. Kelly, Z., Zech, S., Gabbay, M., Thirkill-Mackelprang, A., "Modeling Insurgent Networks using Exponential Random Graphs and Targeting Policies," paper presented at Midwestern Political Science Assoc. conference, Chicago, IL, April 2015.
4. Gabbay, M., "Leadership Network Structure and Influence Dynamics," in *Handbook of Research Methods in Complexity Science: Theory & Application*, E. Mitleton-Kelly, A. Paraskevas, C. Day (eds.), Edward Elgar Publishing (to appear). **(Appendix 3**)
5. Gabbay, M., Kelly, Z., and Zech, S.T., "Ideology, Identity, and Militant Group Networks in Iraq," draft manuscript, 2016. (**Appendix 4**)

5.2 Presentations

1. Gabbay, M., "Modeling Strategic Decision Making in the Afghan Insurgency," 6th Annual Political Networks Conference, Bloomington, IN, June 28, 2013.
2. Gabbay, M., "A Network Model of Insurgent Factional Dynamics," Annual Meeting of the American Political Science Association, Chicago, IL, Sept. 1, 2013.

3. Gabbay, M., “A Simulation of Cooperation and Competition in Insurgent Networks,” American Physical Society March Meeting, Denver, CO, March 7, 2014.
4. Zech, S. and Kelly, Z., “Modeling Insurgent Cooperation Networks using Exponential Random Graphs and Rhetorical Frames,” Center for Social Science and Statistics seminar, U. Washington, April 9, 2014.
5. Gabbay, M. “Theoretical and Empirical Research on Decision Making and Cooperation in Terrorist Networks,” ONR Future Force S&T Expo, Washington, DC, Feb. 5, 2015.
6. Kelly, Z., Zech, S., Gabbay, M., Thirkill-Mackelprang, A., “Modeling Insurgent Networks using Exponential Random Graphs and Targeting Policies,” Midwestern Political Science Assoc. conference, Chicago, IL, April 2015.

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APPENDICES TO FINAL TECHNICAL REPORT

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Appendix 1

PORTEND User Guide

PORTEND

User Guide

Version 1.1

Michael Gabbay

Applied Physics Laboratory, University of Washington

April 2016

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Description

What is PORTEND™?

PORTEND™ (Political Outcomes Research Tool for Elite Network Dynamics) integrates quantitative techniques from complex systems theory and network science to aid the analysis of policy and factional outcomes with respect to the internal dynamics of a system of political actors. The political actors may be individual leaders or organizations within a government or movement. The outcomes of concern may be policy decisions, winning and losing factions, the positions of individuals, or the potential for issues to cause dissension or factional realignment.

Political actors are represented mathematically with respect to their preferences on one or more issues, the saliences of those issues, the network of inter-actor influence relationships, and actor power and susceptibility to influence. The data from which these quantities are calculated is obtained from surveys given to Subject Matter Experts (SMEs). PORTEND™ imports these surveys and aggregates them to form a composite SME if desired. It then allows for structural analysis regarding issues and the inter-actor network and for the simulation of group decision making and influence among actors. The analyses can be performed for individual SMEs allowing for comparison of the implications of different SME viewpoints and for a composite SME as a representation of the average SME view.

There are two different areas, issue and network, of structural analysis. Issue analysis uses statistical metrics, matrix decomposition, and visualization to identify contentious issues, actor alignments on individual issues and patterns of alignments across issues. Network analysis uses social network analysis methods to assess actor influence, visualize network structure, and integrate issue and network data to reveal how issues and network structure align or the special roles or positions of particular individuals as bridges or swing players. The simulation uses a model of nonlinear influence dynamics on a social network to model how actor positions change as a function of actor preferences and the network of relationships between actors. These positions can be aggregated to yield a final group policy and whether individual actors support or dissent from the policy.

Analysis Applications

The following are the types of questions that PORTEND™ can be used to help address:

- Strategic policy making
- Group dissension and stability
- Decision stability
- Identifying key players
- Wedge and realignment issues
- Scenario analysis
- Sensitivity analysis
- Succession analysis
- Alliance formation (inferred)

Further Reading

1. M. Gabbay, “Modeling Decision-Making Outcomes in Political Elite Networks,” in K. Glass et al (Eds.), *Complex Sciences*, 95-110, Springer International Publishing, 2013. An overview of the methodology used in PORTEND™ as applied to Afghanistan government and insurgent actors.
2. M. Gabbay, “A Dynamical Systems Model of Small Group Decision Making,” in *Diplomacy Games: Formal Models and International Negotiations*, Zartman, I.W., and Avenhaus, R. (eds.), Springer, New York, 2007. A description of the nonlinear influence model and its nonlinear behavior.
3. M. Gabbay, “The effects of nonlinear interactions and network structure on small group opinion dynamics,” *Physica A* 378, 118-126, 2007. A mathematical treatment of the nonlinear influence model.
4. M. Gabbay and A. Das, “Majority rule in nonlinear opinion dynamics,” in In, V, Palacios, A. & Longhini, P. (Eds.), *International Conference on Theory and Application in Nonlinear Dynamics (ICAND 2012)*, 167-179, Springer International Publishing, 2014. A mathematical analysis of a phenomenon in the nonlinear influence model where asymmetric majority rule outcomes can arise from symmetric initial conditions.
5. M. Gabbay, “The Rabbani Assassination: Taliban Strategy to Weaken National Unity?”, *CTC Sentinel* 5(3), p. 10-14, March 2012. A policy-oriented article on Afghanistan that draws from results of the PORTEND™ methodology.
6. M. Gabbay, “Mapping the Factional Structure of the Sunni Insurgency in Iraq,” *CTC Sentinel* 1(4), 10-12, March 2008. An analysis of the Iraqi insurgency employing rhetoric (not SME) based factional maps, a component of the PORTEND™ methodology.
7. M. Gabbay, “Application of a Social Network Model of Elite Decision Making,” paper presented at the Annual Meeting of the International Studies Association, Chicago, IL, Feb. 28-Mar. 3, 2007. An application to Russian succession in 2006-07.

Getting Started

Installation

These instructions are for installing PORTEND™ as a MATLAB® app that to be run while MATLAB® is open.

1. Place the installation file `PORTEND.mlappinstall` in the MATLAB® user directory (not the program directory). On Windows, the default user directory is typically `C:\...\Documents\MATLAB`.
2. On the *Apps* tab, click on the *Install App* icon and open `PORTEND.mlappinstall`.
3. Click *Install* on the dialog box. PORTEND™ will now be installed in the `Apps` directory. The PORTEND™ icon appears on the Apps toolbar which can be used to launch the program.
4. To make the user guide contents visible, you must add PORTEND™ to the MATLAB® path: On the *Home* tab, click on *Set Path*. Then select *Add with Subfolders...*, navigate to `MATLAB\Apps\PORTEND` and select it. Then press *Save* and close the *Set Path* window.

To uninstall PORTEND™, right click on its icon and select *Uninstall*.

Help

The complete user guide can be accessed as follows:

1. Open the MATLAB® help window by clicking on the ? icon at the upper right of the command window.
2. Click on *Supplemental Software*.

Help for the major PORTEND™ interfaces can be accessed by clicking the ? icon in the upper left of the interface window.

Examples

The following examples can be used to learn how to conduct analysis and simulation:

- Issue Analysis Example
- Network Analysis Example
- Nonlinear Influence Simulation (1D) Example

Workflow

Workflow Overview

Launching Operations

Launching case management, structural analysis, and simulation tasks.

Workflow Overview

PORTEND™ takes as its input, surveys completed by Subject Matter Experts (SMEs) concerning a given set of political actors. Once the completed surveys are on hand, a typical workflow to analyze and simulate the data would then be as follows:

1. **Set up the case.** Define information needed to generate output; import and aggregate surveys.
2. **Analyze actor positions on issues.** Identify contentious issues, actor alignments on specific issues, and patterns of alignments across issues.
3. **Analyze inter-actor influence network.** Assess actor influence, factional composition, and how issues align with network structure.
4. **Simulate outcomes.** Assess group policy outcomes, supporters, and dissenters.

Once the case is set up, any of steps 2-4 can be conducted. In practice, it is helpful to do the structural analyses of steps 2 and 3 first in order to better guide the simulation. All of these steps are launched from the PORTEND™ Main Window.

A *Case* is the system that PORTEND™ uses to structure the information regarding a given actor set. It is possible to import new surveys to an existing case provided that they are of the same format as the previous ones. Changes in survey format such as adding new actors require a new case be set up.

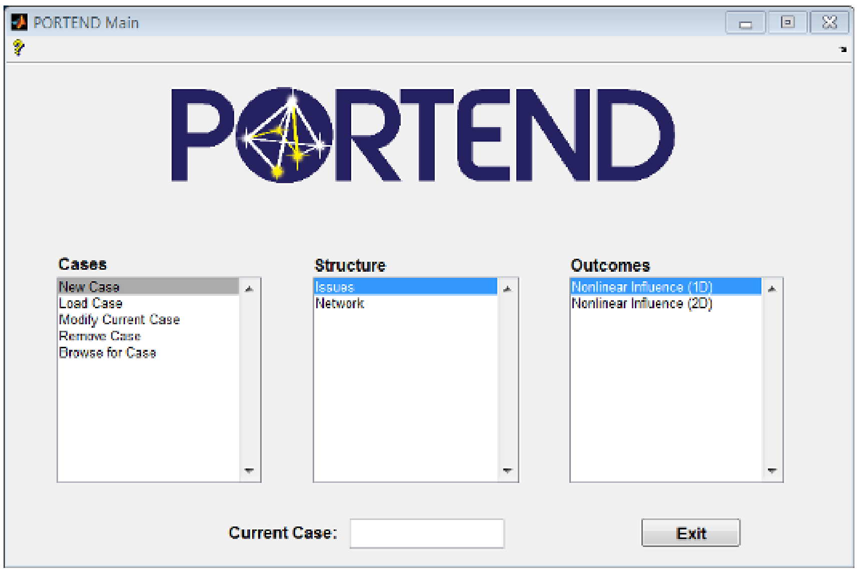
Structural Analysis and Outcome Simulation generate outputs in the form of plots and tables, both of which can be saved. Plots can be annotated using the MATLAB® figure window which also allows for export to a number of graphics file formats. Tables can be saved in MATLAB® or Excel® formats which allows for further analysis. In addition, structural analysis and outcome simulation typically save detailed data in the form of MATLAB® arrays.

Launching Operations

Launching point for case setup and management, structural analysis, and outcome simulation tasks.

Main Window

The image below shows the PORTEND™ main window which appears on startup.



It consists of three menus which launch different types of tasks:

1. **Cases:** Set up a new case. Load, modify, or delete existing cases.
2. **Structure:** Analyze the structure of the issue space or influence network.
3. **Outcomes:** Conduct simulations of policy dynamics and actor position change.

The actions in these menus are accomplished by clicking on the items.

Case Management

Case management is accomplished using the **Cases** menu which consists of the following actions:

- ***New Case*** launches the Case Setup window which is used to define the case name, actors, survey parameters and policies and to import surveys and aggregate surveys.
- ***Load Case*** loads a case for analysis and simulation. It opens a window of existing cases contained in the case list file (`caselist.mat`). Selecting a case and clicking `OK` loads the case and displays its name in the **Current Case** window.
- ***Modify Current Case*** allows you to make changes to the currently loaded case using the Case Setup window. This could involve, for instance, completing unfinished setup steps, changing actor symbols or policy labels, or importing new surveys.

- ***Remove Case*** deletes a case from the case list. No files associated with the case are deleted. A removed case can be loaded using *Browse for Case* if its case information file has not been deleted.
- ***Browse for Case*** opens a case that is not on the case list. A file browser is opened which can be used to load the case information file. The case is re-added to the list of cases.

Structural Analysis

Structural analysis of issues and networks is accomplished using the **Structure** menu. It includes the following actions:

- ***Issues*** allows you to conduct various analyses involving the distribution of actor positions across issues. It opens the Issue Analysis window.
- ***Network*** allows you to analyze and visualize network structure by itself and in relation to actor positions on issues. It opens the Network Analysis window

Outcome Simulation

Simulation of individual and group policy outcomes is accomplished using the **Outcomes** menu. The following simulations are available:

- ***Nonlinear Influence (1D).*** Nonlinear group decision making simulation for a single issue. It opens the Nonlinear Influence Simulation (1D) window.
- ***Nonlinear Influence (2D).*** Not yet implemented.

Case Preparation

Case Basics

Overview of case system for organizing input.

Case Setup and Modification

Setting up a new case or modifying an existing one.

Case Basics

Description

A *case* is the strucure by which PORTEND™ organizes the information needed to conduct analysis and simulation on the set of actors for which a specific survey was designed. The basic input for a case consists of setup information and the actual data from the SME surveys. The setup information consists of survey items such as the list of actors, issues, statements, etc. and user-contributed information needed to construct output such as actor abbreviations and plot symbols. The SME data is imported as part of the setup process

Setup Process Overview

Case setup is accomplished using the Case Setup interface. The setup information is generated and stored in the *case information file*. SME surveys are imported into MATLAB® format. Case Setup also allows for the construction of composite SMEs.

In order to fully set up a case for analysis and simulation, at least one completed SME survey is needed.

You should also have ready beforehand an association of issues and attitude statements (which should have been designed into the survey in the first place). If you wish to designate qualitative policy names for locations on the issue axis, then an association of policies and statements should be on hand (unless you as a user directly assign policies to locations). If actors can be clearly placed into categories due to, for instance, common ethnic or organizational membership, having such a categorization ready is useful for assigning common shapes and/or colors to actor plot symbols if desired.

In the case setup process, the user first specifies a case name and directory. You can then enter information about the survey needed to import data from each of its component worksheets such as specifying worksheet names and data table cells. Once this is accomplished SME surveys can be imported. The survey is also used to import actor names. The user defines actor abbreviations and symbols and the default leader. Another element of the process is the association of issues and attitude statements necessary to calculate actor issue positions. A composite SME can be optionally formed using several different weighting schemes. Another optional element is the assignment of qualitative policy labels to either attitude statements, allowing for the calculation of policy locations on the issue axis for each SME, or directly to issue axis locations.

Directory Structure

The case directory is intended to house both input and output. However, with the exception of the case information file, there is flexibility as to where you can store input and output files. The case directory includes the following input-related subfolders:

- `info`: This contains the case information file. It is required.
- `input`: This is the default location for the imported SME surveys. You can navigate to a different folder if desired.

The current working directory is the default directory in which output is saved. You can navigate to the desired output folder.

The list of all cases is contained in a file called `caselist.mat` which resides within the `userinfo` subfolder of the PORTEND™ program folder. Cases can be managed using the *Cases* menu of the PORTEND™ Main Window.

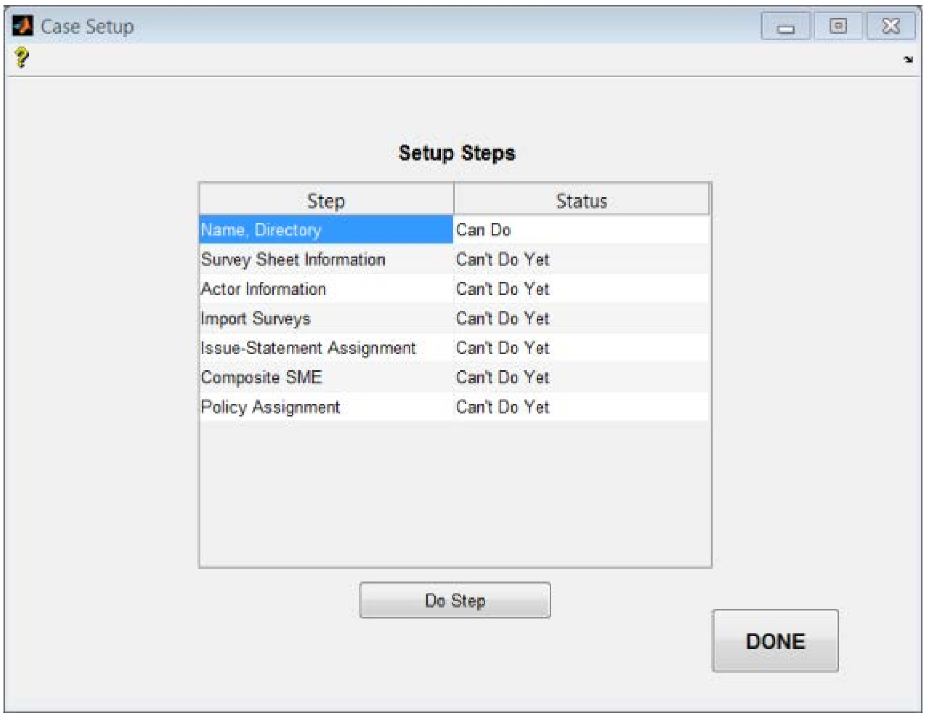
Note: The case directory must not be placed within the PORTEND™ program folder structure.

Case Setup and Modification

Set up a new case or modify an existing case.

Interface

The image below shows the Case Setup interface. It is launched from the PORTEND™ Main Window by selecting *New Case* or *Modify Current Case*.



It consists of the following steps:

1. **Name, Directory:** Choose case name and directory.
2. **Survey Sheet Information:** Enter information about survey worksheets.
3. **Actor Information:** Define actor abbreviations and other information.
4. **Import Surveys:** Import data from survey spreadsheets.
5. **Issue-Statement Assignment:** Associate survey attitude statements with issues.
6. **Composite SME:** Aggregate SME surveys.
7. **Policy Assignment:** Define issue policy labels and information for associating policies with issue axis positions.

Setup Steps

Setup steps are initiated by selecting the step and pressing the **Do Step** button which will open up the associated window. Some of the steps are prerequisites for others. If an uninitiated step's prerequisites have been completed, its status will read "Can Do." Otherwise, it will read "Can't Do Yet." For a new case, *Name, Directory* must be conducted first. When modifying an already fully setup existing case, any step can be executed.

The steps are briefly described below; prerequisites are noted and whether the step has to be fully completed once initiated. Detailed help files for each of the steps is available.

***Name, Directory*.** Choose case name and directory where input and other files will be stored. Prereqs: None. Must be fully completed or cancelled.

***Survey Sheet Information*.** Enter information needed in order to import surveys such as worksheet names and data cell ranges. Prereqs: *Name, Directory*. Can be completed over multiple sessions (data for different worksheets can be entered at different times).

***Actor Information*.** Define actor information needed for plots and tables - abbreviations, symbols, colors - and choose default leader. Prereqs: *Name,Directory*. Must be fully completed or cancelled.

***Import Surveys*.** Import SME surveys into MATLAB® data arrays. Prereqs: *Survey Sheet Information*. Surveys can be imported at different times. Also, opening this window does not require you to import a survey.

***Issue-Statement Assignment*.** Associate attitude statements on the survey with the issues they correspond to and test significance. Assign issue abbreviations. Prereqs: *Import Surveys*. Can be completed over multiple sessions. However all issues listed in the survey must be completed before doing structural analysis or simulation.

***Composite SME*.** Form a composite SME by aggregating individual SME surveys. Several aggregation methods are available. Prereqs: *Actor Information, Import Surveys*. Composite SMEs can be formed at different times. Opening the window does not require a composite SME be formed.

***Policy Assignment*.** Define a set of policy labels for each issue and how their issue axis coordinates should be calculated. Prereqs: *Actor Information, Issue-Statement Assignment*. Different issues can be completed at different sessions. *Policy Assignment* is not needed to conduct simulations (it is not used for structural analysis).

Notes

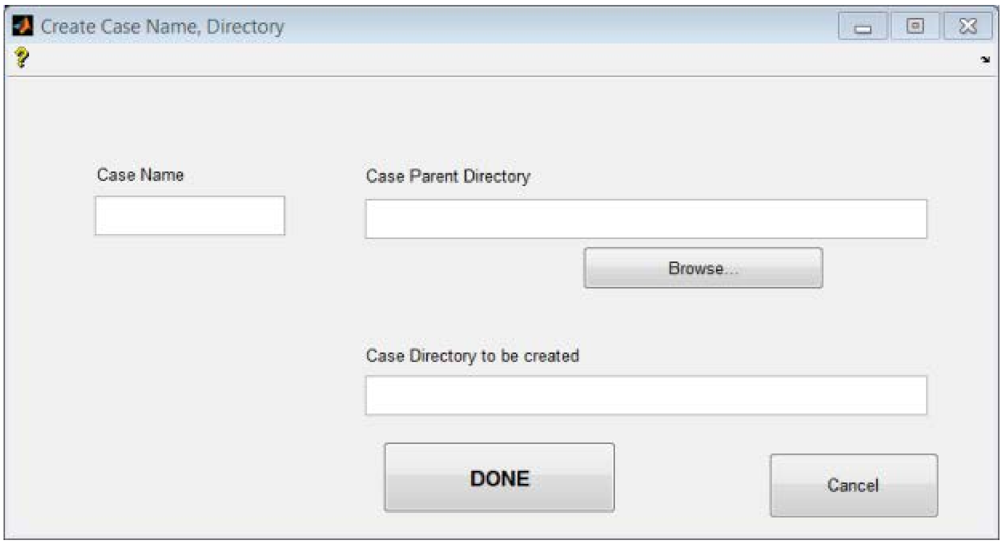
1. For steps that can be completed at multiple times, a status of "Done" will be displayed even if not all elements of the step have been performed. For instance, if only some of the worksheets have been completed under *Survey Sheet Information*, the status will read "Done." This will enable *Import Surveys* to be performed but only the completed worksheets can be imported.

Create Case Name and Directory

Assign a name and directory for a new case.

Interface

The image below shows the Create Case Name, Directory interface. It is launched from the PORTEND™ Case Setup.



The user can edit the following fields:

1. **Case Name:** Enter case name.
2. **Case Parent Directory:** The parent directory within which the case directory will be created.

Components

Case Name. Type the name of the case here. The case name must begin with a letter and contain only letters, numbers, and underscores.

Case Parent Directory. Type the name of the case parent directory including the full path here or select using the directory browser.

Case Directory to be created. Full path name of the directory to be created. A subdirectory called `info` will be created in which the case information file will be saved. The case information file contains the information needed to run analyses and simulations. It is given the name `MyCase_caseinfo.mat` where `MyCase` is the name entered in *Case Name*.

DONE. Creates the case directory, `info` subdirectory, and case information file.

Notes

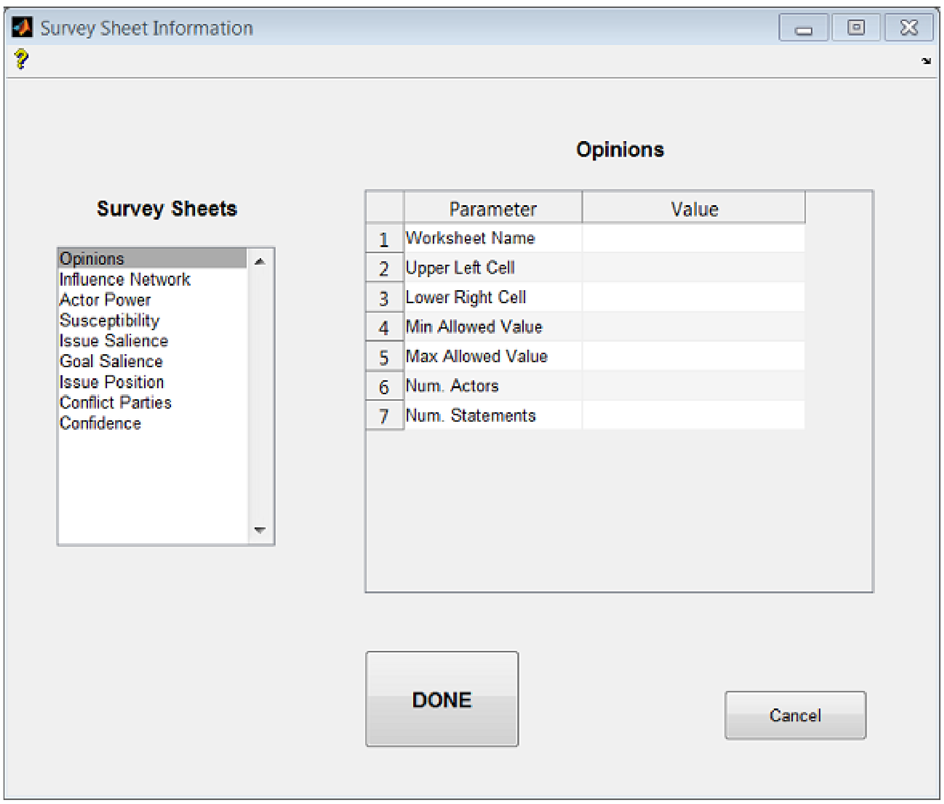
1. While only the case information file is required to reside within the case directory structure, it is recommended that you import survey data here. Output files may be placed here as well.
2. Do not change the case name or directory from within your system file browser. If you wish to change the case name or directory, do so using this interface. This will create a new case information file with all of the existing case information (apart from new name and directory). If you wish to transfer any other subdirectories apart from `info`, you can use your system file browser to do so. However, the default directories used in some interfaces, such as for input arrays, will still be as originally assigned (but you can navigate to the new ones from the interfaces)
3. Placing the case directory within the PORTEND™ program directory is not recommended.

Survey Sheet Information

Enter information needed in order to import surveys.

Interface

The image below shows the Survey Sheet Information interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Survey Sheets:** Select worksheet type from list.
2. **Worksheet Parameter Table:** Enter parameter values for selected worksheet.

Pressing the ***DONE*** button saves the worksheet information in the case information file. Different worksheets can be completed at different sessions.

Survey Sheets

Selecting a worksheet from the list of available types in the **Survey Sheets** menu presents the associated parameters in the adjacent table (see next section). The worksheet types are defined below. Worksheet types that are required to conduct structural analyses and simulations are noted.

- ***Opinions.*** Actor responses to attitude statements. Required.
- ***Influence Network.*** Network of dyadic influence weights. Required.
- ***Actor Power.*** Actor power scores. Required.
- ***Susceptibility.*** Actor susceptibility to influence from other group members. Required.
- ***Issue Salience.*** Saliences of issues to each actor. Required.
- ***Goal Salience.*** Salience of goals to each actor. Not yet supported for analysis and simulation.
- ***Issue Position.*** Direct scoring of actor issue positions. Not yet supported for analysis and simulation.
- ***Conflict Parties.*** Actor identities relative to in and out-groups. Not yet supported for analysis and simulation.
- ***Confidence.*** SME self-assessment of confidence in answers about each actor. Required.

Worksheets can be completed in any order.

Worksheet Parameters

The worksheet parameters are defined below. Parameters which only appear on particular worksheets have the specific sheets noted in parentheses.

- ***Worksheet Name.*** Name of the worksheet as it appears in the survey.
- ***Upper Left Cell.*** Top and leftmost cell of the table containing the user-entered data. For example, C12.
- ***Lower Right Cell.*** Fottom and rightmost cell of the table containing the user-entered data. For example, Q26.
- ***Min Allowed Value.*** Minimum value that the user is allowed to enter.
- ***Max Allowed Value.*** Maximum value that the user is allowed to enter.
- ***Num. Actors.*** Number of actors.
- ***Num. Statements.*** Number of attitude statements. (Opinions)
- ***Num. Issues.*** Number of issues. (Issue Salience)
- ***Num. Goals.*** Number of goals. (Goal Salience)
- ***Num. Parties.*** Number of conflict parties (Conflict Parties)

Notes

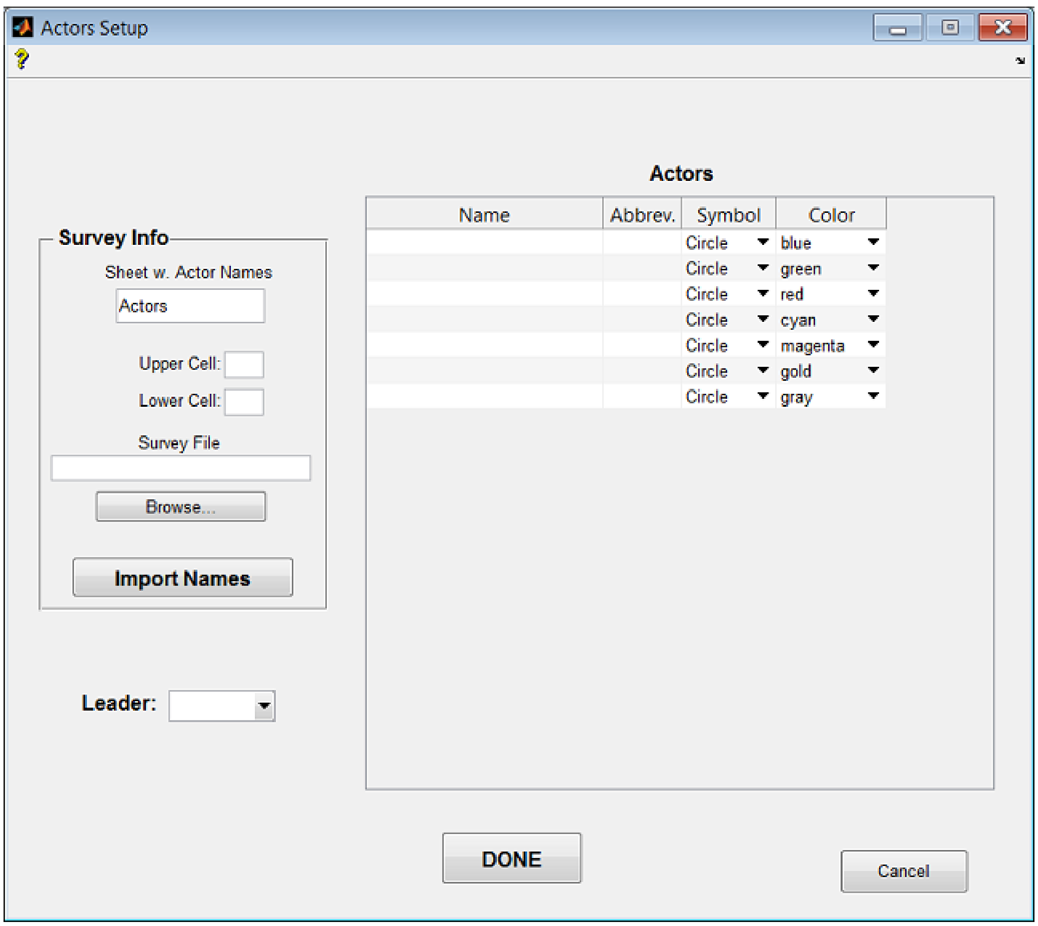
1. A limited amount of error checking is performed when the ***DONE*** button is pressed with respect to missing parameter values and invalid formats. Any problems found are listed and presented to the user. You then are given the choice of whether you want to fix the problems or use the values as is. The latter option is available so as not to be overly restrictive on worksheet formatting but should be used with caution.
2. Worksheets not on the survey need not be defined.

Actors Setup

Define actor information needed for plots and tables and choose default leader

Interface

The image below shows the Actors Setup interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Survey Info:** Enter survey information for importing actor names.
2. **Actors:** Enter actor abbreviations; select plot symbols, and colors.
3. **Leader:** Select the default group leader.

Pressing the ***DONE*** button saves the actor information in the case information file. The requested information for all actors must be completed.

Survey Info

Actor names are imported from the survey using **Survey Info**.

The panel consists of the following elements:

- ***Sheet w Actor Names.*** Enter the name of the worksheet that contains the actor names here. The default is "Actors."
- ***Upper Cell.*** The cell containing the name of the first actor.
- ***Lower Cell.*** The cell containing the name of the last actor.
- ***Survey File.*** Full path name of the survey file to be used for importing the actor names. It can be typed in or selected using Browse button.
- ***Import Names.*** Executes actor name importation.

Actors

Actor names, abbreviations, symbols, and colors are designated using the **Actors** table. It consists of the following columns:

- ***Name.*** Imported actor names will be listed here. Actor names can then be manually edited if desired.
- ***Abbrev.*** Enter the abbreviations used to designate actors on plots and tables here. For best legibility, abbreviations should be three characters or less although longer ones are allowable.
- ***Symbol.*** Choose the symbols used to represent the actors on plots. Choices are: Circle, Square, Diamond, Upward-pointing Triangle (Up Tri.), Downward-pointing Triangle (Down Tri.)
- ***Color.*** Choose the color for actor symbols and lines on plots. Choices are: blue, green, red, cyan, magenta, gold, gray.

Note: It can be visually helpful to designate actors belonging to a common faction, ethnic group, etc. by the same symbol and/or color.

Leader

The default group leader is selected using the **Leader** menu. The actor abbreviations appear in the menu once they have been entered in the **Actors** table. The leader is used for the *Leader Choice* decision rule in simulations. A default leader must be selected. However, the leader can be changed when running simulations (or is irrelevant when an alternate decision rule is used).

Notes

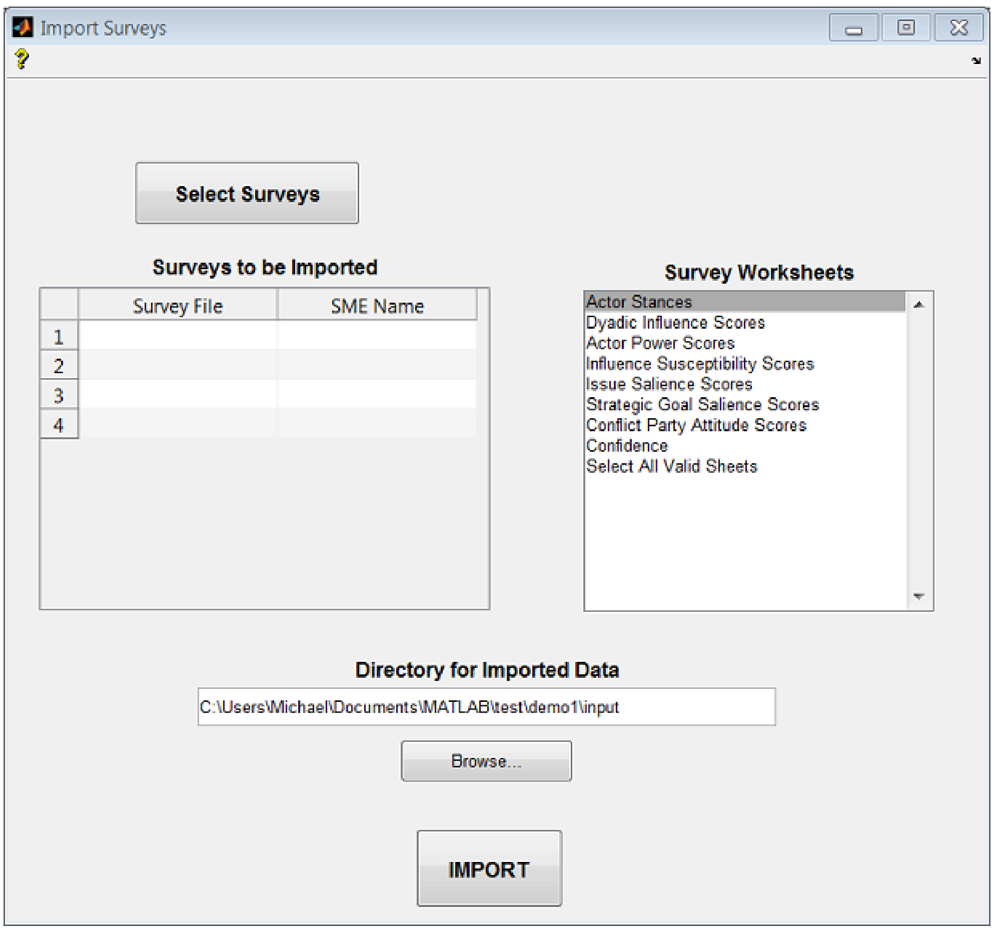
1. Actor information from an existing case can be revised using the **Actors Setup** interface.
2. Do not change the order of actors from that in the survey.
3. Do not delete actors. Capability for excising actors is provided within the analysis and simulation interfaces.

Import Surveys

Import completed SME survey spreadsheets into MATLAB format.

Interface

The image below shows the Import Surveys interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Select Surveys/Surveys to be Imported:** Select and name SME surveys to be imported.
2. **Survey Worksheets:** Select worksheets to be imported.
3. **Directory for Imported Data:** Select directory into which SME data will be imported.

Pressing the **IMPORT** button imports the surveys. Surveys can be added at different times.

SME Survey Selection and Naming

SME surveys for importation are chosen by pressing ***Select Surveys***, navigating to the folder where the surveys are located, and selecting one or more surveys. The survey file names are listed under *Survey File* in the ***Surveys to be Imported*** table.

The *SME Name* column is used to assign names to the files that will be created. For example, if the SME name is "Mary" then the file `Mary_inp.mat` will be created. An SME name must begin with a letter and contain only letters, numbers, and underscores. The SME name is used to identify SMEs on plots and tables.

Survey Worksheets

The specific worksheets desired to be imported can be selected using the ***Survey Worksheets*** menu. The worksheets are listed by the names on the actual survey. *Select All Valid Sheets* will import all the worksheets for which parameters have been defined using the Define Survey Sheets interface.

Directory for Imported Data

The directory in which the files containing the imported data are placed can be selected here. The default directory is `MyCaseFolder/input` where `MyCaseFolder` is the case directory created using the Create Case Name, Directory interface.

Notes

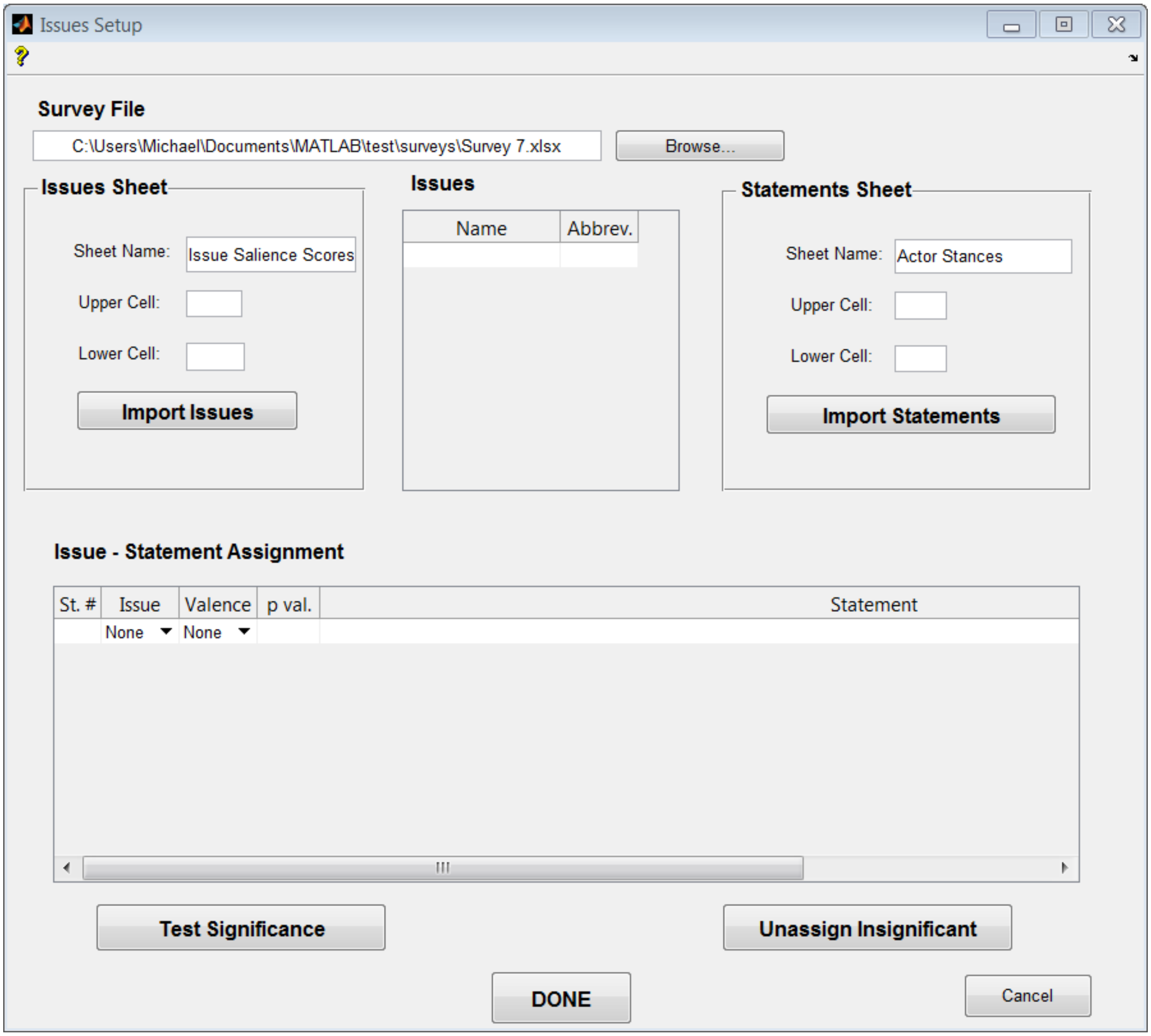
1. Using the `MyCaseFolder/input` default directory for the SME data files is recommended (in order to facilitate transferring files when renaming a case).

Issues Setup

Assign attitude statements to issues.

Interface

The image below shows the Issues Setup interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Survey File:** Select survey for importing issues and statements.
2. **Issues Sheet:** Import issue names.
3. **Issues:** Assign names and abbreviations to issues.
4. **Statements Sheet:** Import attitude statements.
5. **Issue-Statement Assignment:** Associate statements with issues and test for statistical significance.

Pressing the **DONE** button checks for problems and, if none, saves the assignments to the case information file. A successfully saved issue-statement assignment can be subsequently revised.

Selecting Survey

The survey to be used for importing issue names and statements can be selected using the *Browse* button and appears in the **Survey File** box.

Importing Issues and Statements

Issue names are imported using the **Issues Sheet** panel. The text of attitude statements is imported using the Statements Sheet panel. The following fields must be completed:

- ***Sheet Name.*** The name corresponding to the Issue Salience or Opinions worksheet types for issue names and statements respectively.
- ***Upper Cell.*** The cell containing the first issue name or first statement text as appropriate.
- ***Lower Cell.*** The cell containing the last issue name or last statement text as appropriate.

Pressing ***Import Issues*** places the issue names under the *Name* field in the **Issues** table and populates the *Abbrev* field using the first four (allowed) characters of the imported issue names. The abbreviations appear in the *Issue* menu of the **Issue-Statement Assignment** table.

Pressing ***Import Statements*** populates the statement number and statement text fields of the **Issue-Statement Assignment** table.

Editing Issue Names and Abbreviations

Issue names and abbreviations can be manually entered or edited in the **Issues** table. Issue names are used in plots. Issue abbreviations are used in plots, tables, and file names. Issue abbreviations must begin with a letter and contain only letters, numbers, or underscores.

Note: After editing an issue abbreviation, make sure to click outside the edited cell. This enters the edit and updates the ***Issue*** menu in the **Issue-Statement Assignment** table.

Assigning Statements to Issues

The position of an actor on an issue (the *natural preference* in the nonlinear influence simulation) is calculated as the average of the actor's responses over all the statements assigned to that issue. After importing issues, defining abbreviations, and importing statements, issues and statements are associated using the **Issue-Statement Assignment** table. The fields of table are as follows:

- ***St. #.*** Statement number.
- ***Issue.*** Select which issue (or 'None') from the pull-down menu.
- ***Valence.*** Select the sign, positive ('Pos') or negative ('Neg'), reflecting the valence of the statement for the issue. A positive (negative) valence signifies that the statement expresses an attitude supporting (opposing) the positively-defined side of the issue. A statement assigned to an issue cannot have a valence of 'None.'
- ***p val.*** Statistical significance resulting from execution of ***Test Significance***.
- ***Statement.*** Statement text.

Test Significance calculates, for each statement assigned to an issue, the statistical significance of the correlation between the actors' positions on the issue and the actors' responses to the given statement. It is expected that a statement which clearly expresses a positive or negative attitude on the issue will have a statistically significant correlation whereas lack of significance indicates the statement is ambiguous with respect to the issue. The user is prompted to enter a threshold significance level after the ***Test Significance*** button is pressed (Default: .05).

Unassign Insignificant unassigns statements whose sigificance level falls below the threshold. Insignificant statements need not be removed. Statments can also be removed or reassigned manually.

Note: All issues must be assigned statements but not all statements need be assigned to issues. Good survey design practice calls for ensuring that all issues have corresponding statements in the survey.

Procedure

The following sequence of steps should be followed:

1. Import issues.
2. Edit issue names and abbreviations.
3. Import statements.
4. Assign issues and valences to statements
5. Test significance.
6. Revise statement assignments via ***Unassign Insignificant*** or manually.
7. Press ***DONE***.

Notes

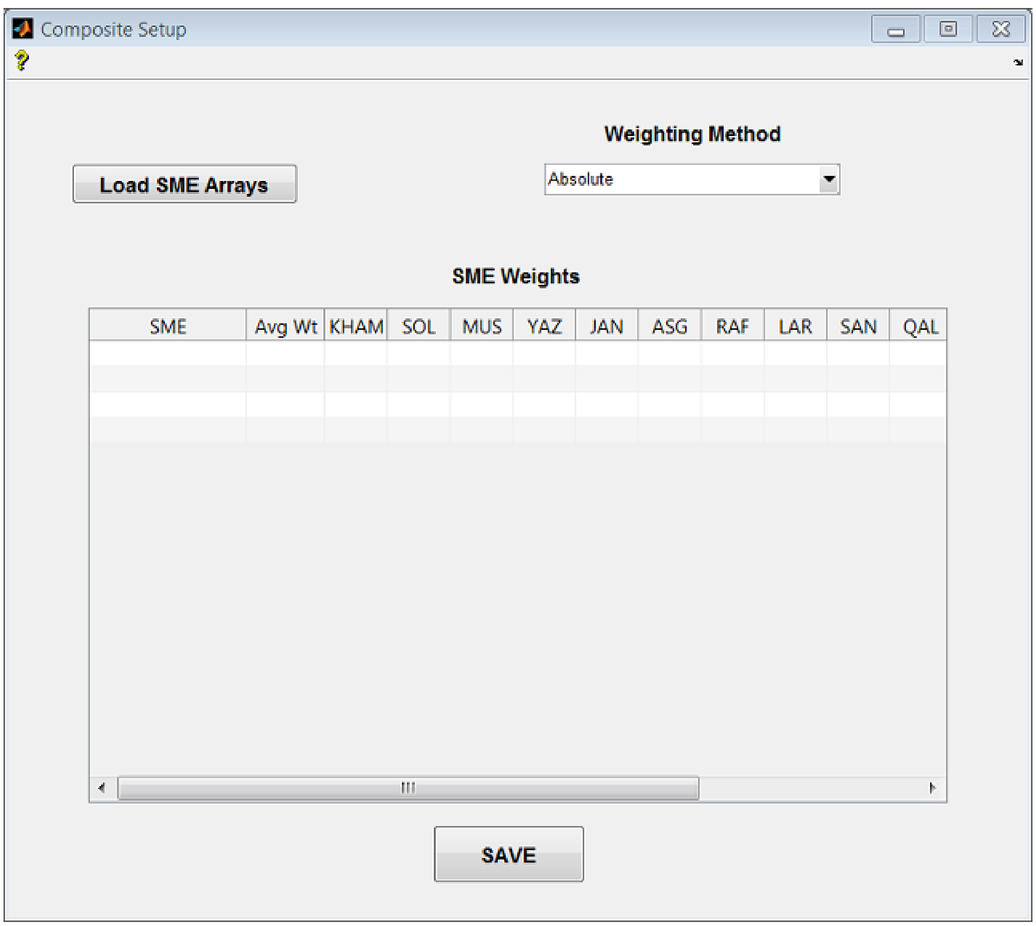
1. Sequential completion of **Issues Setup** is possible as long as all issues have been assigned at least one statement during the initial setup. The assignments can then be saved and additional assignments made later.
2. Re-importation of issues after issue-statement assignment is not recommended as it may cause problems with the ***Issue*** menu. It is preferable to manually edit issue names and abbreviations after initial importation.

Composite Setup

Form aggregate SME from individual SMEs.

Interface

The image below shows the Composite Setup interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Load SME Arrays:** Select SME arrays to aggregate.
2. **Weighting Method:** Select aggregation method.
3. **SME Weights Table:** Weighting of each SME overall and by actor.

4. **SAVE:** Save composite SME array.

Composite SME arrays can be generated at any time once the case setup prerequisites have been met.

Load SME Arrays

Pressing **Load SME Arrays** opens up a file browser at the directory specified in the Import Surveys interface. Select at least two arrays of individual SMEs to aggregate. These files will be of the form `SMEname_inp.mat` where `SMEname` is the name the user has given to the individual SME.

Weighting Method

The composite SME is formed by a weighted average of the survey responses for each individual SME. For methods using the SME self-assessment of how confident he or she is on each actor (the ***Confidence*** worksheet), the weights are calculated on an actor-by-actor basis.

Selecting a method from the **Weighting Method** menu will execute that method. The following methods are available:

- ***Absolute.*** SME weights for each actor are determined by the absolute confidence value for that actor. Prior to averaging, the confidence scores are normalized so that the sum for each actor is one. This method assumes that the absolute magnitude of the SME confidence scores accurately reflect true knowledge levels so that, for instance, a SME whose confidence score for an actor is 4 will be given twice as much weight than whose confidence score is 2. Consequently, the method runs the risk that overconfidence is construed as greater expertise.
- ***Egalitarian.*** This method assumes that only variations in the confidence scores assigned to actors within The confidence scores for each SME are normalized so that the sum over actors is one. These scores are then further normalized to sum to one for each actor. The method assumes that all SMEs are equally knowledgeable: they are all given the same total weight (but the weights can vary by actor). This method can compensate for overconfident SMEs but runs the risk of ignoring genuine differences in expertise.
- ***User Specified.*** The user sets the weighting for each SME. The scale is from 1 to 10. The confidence scores are first normalized so that they sum to one for each SME. Each SME's scores are then multipled by the user weight followed by a normalization so that the SME weights for each actor sum to one. If all SMEs are assigned the same weight then this is the same as the *Egalitarian* method.
- ***Mean.*** Aggregation is performed as the straight average over SME survey response. No SME or actor-dependent weighting is used.

For all methods, blank data cells present on the survey for a given SME are not included in the averaging process.

SME Weights Table

The **SME Weights** table lists the following for each SME used in the aggregation:

- ***Avg Wt.*** The average of all the individual actor weights.
- ***Actor Weights.*** The weight of the given SME used in calculating the average for that actor. The actor weights sum to one for each actor.

Note: For the ***Egalitarian*** method, one might expect that the average weight for each SME would be the same, namely, *1/M* where *M* is the number of SMEs. However, the values need not be exactly *1/M* although they are typically close. Similarly, the average weights for the ***User Specified*** method need not be exactly in proportion to the user weights.

Saving

The **SAVE** button opens up a new window in which the user is prompted to enter:

- ***Composite SME Name.*** A name for the composite SME. The saved file will be called `ComposName_inp.mat` where `ComposName` is the user-assigned name. A default name is given of the form `Compos_method` where `method` is a suffix denoting the weighting method ('abs', 'egal','user', 'mean').
- ***SME Arrays Directory.*** Directory into which the composite SME file will be saved. The default is the same directory as the individual SME files are stored in.

Pressing **SAVE** on this window saves the file. If there is a duplicate file name, it will be automatically overwritten without a prompt.

Procedure

The following sequence of steps should be followed:

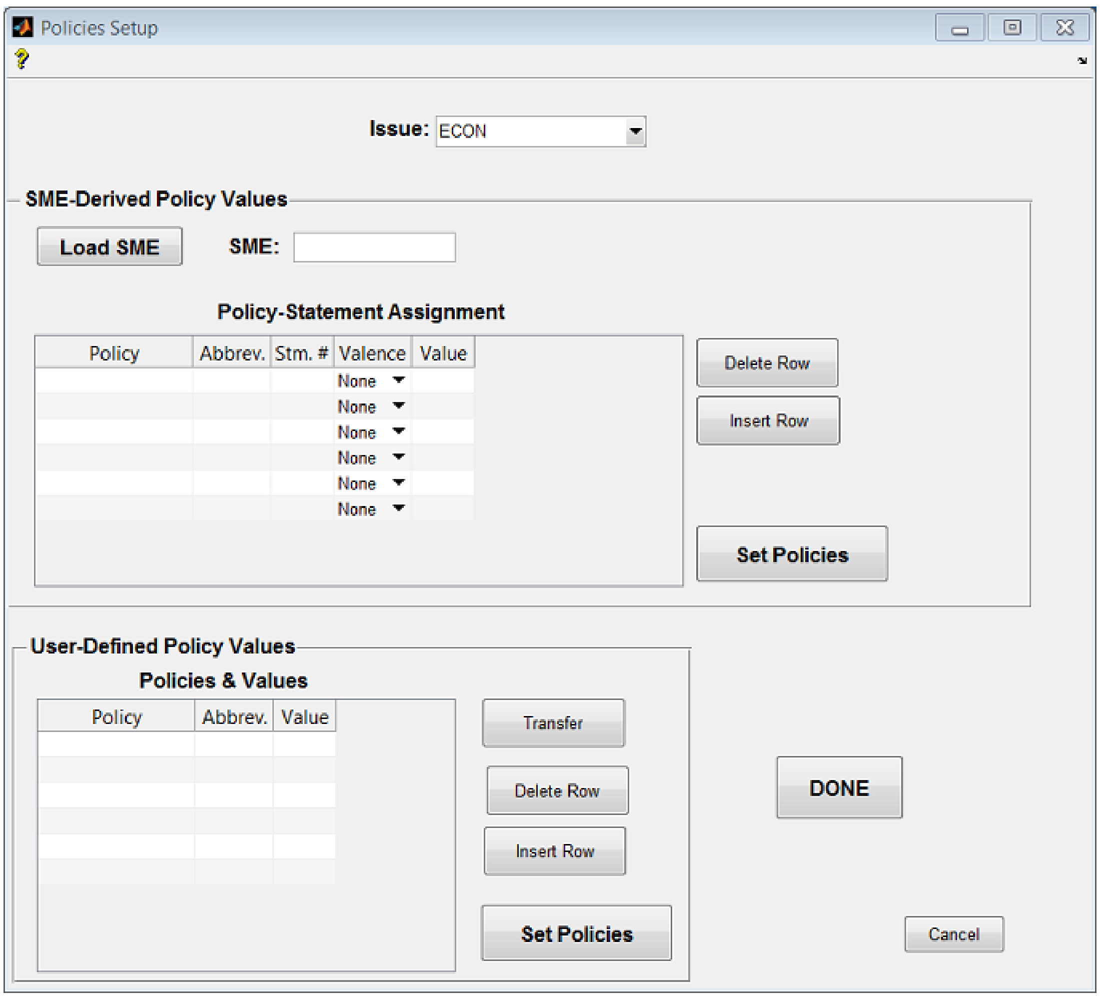
1. Load SME arrays.
2. Select weighting method.
3. Save if desired.

Policies Setup

Define policy names and values for an issue.

Interface

The image below shows the Policies Setup interface. It is launched from the PORTEND™ Case Setup window.



It consists of the following main components:

1. **Issue:** Select the issue for which to set up policies.

2. **SME-Derived Policy Values:** Enter information needed to calculate policy locations from SME data.
3. **User-Defined Policy Values:** Enter user-defined policy locations.

Pressing **DONE** saves the policy information to the case information file. At least one of either the SME-Derived or User-Defined Policy Values panels must be completed in order to save. Previously saved policy information will appear when **Policies Setup** is rerun for an existing case.

Policies are used to assign labels to regions of the issue axis so that the numerical policy value outcome of a simulation can be interpreted qualitatively. The policy labels do not affect the simulation itself.

SME-Derived Policy Values

This method associates a statement from the *Opinions* worksheet with each policy that is defined for the selected issue. A location for the policy on the issue axis is then calculated as the weighted average of the issue positions (natural preferences) of the actors who support the policy. An actor is taken to support the policy if the actor agrees with the associated statement (or disagrees if the valence is negative). A response expressing strong agreement is weighted twice as much as a response of weak agreement. The policy locations are then used to define intervals for each policy by establishing boundaries between them. The boundary between a pair of adjacent policies is set halfway between the policy locations.

The ***Load SME*** button opens up a file browser which allows you to select the SME to be used for calculating the policy location values. policy values. The SME name appears in the adjacent box.

The **Policy-Statement Assignment** table contains the following columns:

- ***Policy.*** Enter the full name of the policy here.
- ***Abbrev.*** Enter an abbreviated name of the policy to be used on plots. The abbreviations must consist of letters, numbers, or underscores.
- ***Stm. #.*** Enter the number of the statement to be associated with the policy.
- ***Valence.*** Select a positive ('Pos') valence if agreement with the statement reflects support of the policy or a negative ('Neg') valence if disagreement with the statement reflects support of the policy.
- ***Value.*** The calculated policy location for the selected SME. If no actor supports a policy, a location cannot be calculated. The policy values are for inspection purposes and are not saved in the case information file (Policy locations are calculated on the fly every time a simulation is run for a given SME).

Rows can be inserted or deleted using the ***Insert Row*** and ***Delete Row*** buttons.

Set Policies prepares the assignments for saving and calculates the policy location values which appear in the table. It must be pressed prior to proceeding to a different issue or pressing **DONE**.

All SMEs must have the same policy statements and so only one SME need be selected to set the policy statements. Typically, this would be the composite SME. However, it may be desirable to inspect the policy values for different SMEs.

User-Defined Policy Values

This method is used to manually set policy locations. Only one set of user-defined policy values can be defined for a given issue (different SMEs cannot be assigned distinct user-defined policies).

The **Policies & Values** table contains the following columns:

- ***Policy.*** Enter the full name of the policy here.
- ***Abbrev.*** Enter an abbreviated name of the policy to be used on plots. The abbreviations must consist of letters, numbers, or underscores.
- ***Value.*** Enter the policy location value here. Typically, it will be a number within the range of the issue axis, -2 to 2, although it is possible to set values outside this range. The policy values are saved in the case information file (unlike the SME-Derived method) .

The ***Transfer*** button transfers the *Policy*, *Abbrev*, and *Value* columns from the **Policy-Statement Assignment** table if that has been completed. Rows can be inserted or deleted using the ***Insert Row*** and ***Delete Row*** buttons.

Set Policies prepares the assignments for saving. It must be pressed prior to proceeding to a different issue or pressing **DONE**.

Procedure

The following sequence of steps should be followed. Steps 2-5 correspond specifically to the SME method and 6-7 to the User method. Either one or both can be done.

1. Select issue.
2. **SME-Derived Policy Values:** Load a SME array;
3. Enter policy names and abbreviations;
4. For each policy, enter a statement number and valence;
5. Press **Set Policies**.
6. **User-Defined Policy Values:** Enter policy names, abbreviations, and values;
7. Press **Set Policies**.
8. Press **DONE**.

Notes

1. Policy information is only used for simulation not structural analysis. Policies need not be set up to conduct simulations. In the Nonlinear Influence Simulation interface, the user can select options corresponding to no, SME-Derived or User-Defined policy labeling.
2. Two or more policies may be set up for an issue. The upper limit for the SME-Derived method is set by the number of statements corresponding to distinct policies. There is no upper limit for the User-Defined method.

Structural Analysis

Issue Analysis

Analysis and visualization of actor positions on issues.

Network Analysis

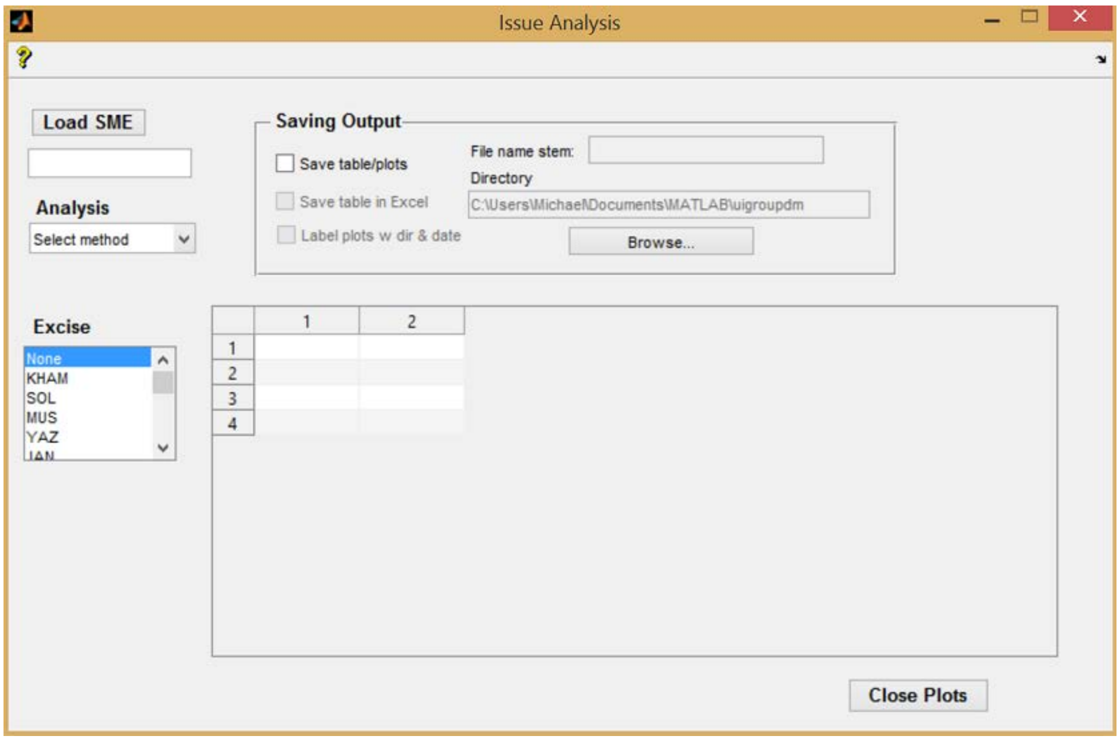
Analysis and visualization of actor influence network.

Issue Analysis

Analysis and visualization of actor positions on issues

Interface

The image below shows the Issue Analysis interface. It is launched from the PORTEND™ [Main Window].



It consists of five components with which the user can interact:

1. **Load SME:** Load an SME input array.
2. **Analysis:** Select analysis method.
3. **Excise:** Exclude selected actors from the analysis.
4. **Saving Output:** Save plots and data tables as analyses are conducted.
5. **Close Plots:** Close all open figures generated by this window.

The central data table displays analysis results in tabular form.

The Issue Analysis interface requires that Issue Setup, Actor Setup, and Survey Import have been conducted.

Loading SME Input

Clicking the **Load SME** button opens a window which allows you to select an SME input array. Only one array can be analyzed at at time. The default directory is that specified when importing the SME surveys using the Survey Import function.

Analysis Methods

Selecting an analysis method from the **Analysis** pull-down menu executes that method (and saves the output if selected). Analysis results are displayed in the data table. Plots, if generated, are opened in separate figure windows.

If a new SME array is loaded, the list of excised actors is changed, or saving output is specified, the selected method must be reselected to perform the analysis with those changes.

The following analysis methods are available.

Standard Deviation. Calculates the standard deviation of actor issue positions for each issue. This is a simple way of assessing how contentious each issue is. The data table displays each issue and its standard deviation.

Issue Plots. Plots actor positions for each issue separately on a 1-dimensional axis. This allows for visual assessment of actor alignment for a given issue and comparison across issues. The data table displays actor positions for each issue.

Cross-Correlation. Calculates for each pair of issues the correlation between actor positions on those issues. This is useful for quantitatively assessing how similar the distribution of actor positions are across issues. The data table displays a table of issue cross-correlations and a table of the statistical significance of those correlations. For each issue pair, a two-dimensional plot of the actor positions on those issues is generated; the correlation and significance are also shown on the plot.

PCA. Performs a Principal Component Analysis on the matrix of actor positions on issues. This allows for assessment and ranking of patterns of correlations across issues and is useful for visualizing issue-based dominant and subordinate factional structure. The data table lists the following information for the first three principal components (PCs): (1) Eigenvalue - a measure of the importance of the PC in the data. (2) Actors and their PC coordinate values sorted by magnitude (not sign). Actors with the largest magnitudes are most important in the PC. Actors with similar coordinates tend to vary their positions in similar ways for the dominant issues in that PC. (3) Issues and their PC coordinate values sorted by magnitude. Issues with large magnitudes in comparison with other are most important in the PC. Actors vary their positions in similar ways for large magnitude issues in the PC.

Three figure windows are generated by *PCA*: (1) A plot of the eigenvalues normalized so that they sum to one. (2) Plots of the actor coordinate values and issue coordinate values for the first three PCs (1 - blue, 2 - green, 3 - red). (3) Plots of the actor coordinate values on a 1-dimensional axis for each of the first three PCs. (4) A 2-dimensional plot of actor coordinates for the first two PCs.

Excising Actors

One or more actors can be excluded from the analysis method calculation and plots by selecting them from the **Excise** menu. The method must be reselected after changing the actors to be excised.

Saving Output

Checking the *Save table/plots* box will save the data table and plots generated in MATLAB® format when an analysis method is performed.

The *File name stem* is the file name under which the data table will be saved and is the stem for the file names of the figures. It defaults to the SME name but can be changed or extended to, for instance, indicate excised actors or other specifics.

The *Directory* is the directory in which files will be saved. It defaults to the current directory.

Checking *Save table in Excel* will also save the data table in .xls format.

Checking *Label plots w dir & date* will place the full file name path and date of the analysis on the bottom of the figure window. This is useful for going back to edit original versions of figures pasted into documents.

Note: Files with same file name already existing in the output directory will be automatically overwritten - no prompt asking whether you wish to do so is given.

Procedure

The basic procedure is as follows:

1. Press **Load SME** and select a SME file.
2. Excise one or more actors using the **Excise** list if desired.
3. If desired, check *Save table/plots* to save the output.
4. Select a method from the **Analysis** menu.

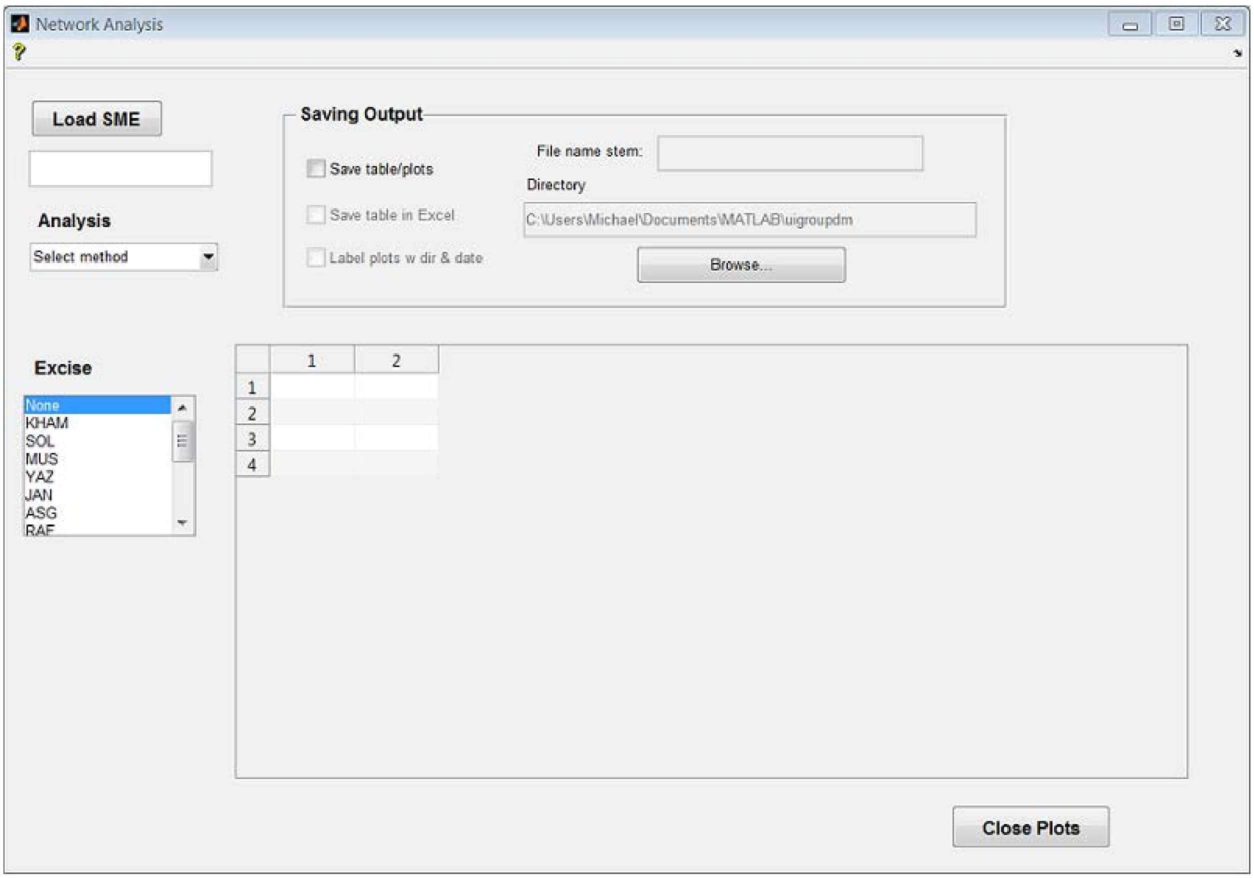
For an example, see Issue Analysis Example.

Network Analysis

Analysis and visualization of actor influence network.

Interface

The image below shows the Network Analysis interface. It is launched from the PORTEND™ Main Window.



It consists of five components with which the user can interact:

1. **Load SME:** Load an SME input array.
2. **Analysis:** Select analysis method.
3. **Excise:** Exclude selected actors from the analysis.
4. **Saving Output:** Save plots and data tables as analyses are conducted.

5. **Close Plots:** Close all open figures generated by this window.

The central data table displays analysis results in tabular form.

The Network Analysis interface requires that Issue Setup, Actor Setup, and Survey Import have been conducted.

Loading SME Input

Clicking the **Load SME** button opens a window which allows you to select an SME input array. Only one array can be analyzed at at time. The default directory is that specified when importing the SME surveys using the Survey Import function.

Analysis Methods

Selecting an analysis method from the **Analysis** pull-down menu executes that method (and saves the output if selected). Analysis results are displayed in the data table. Plots are opened in separate figure windows.

If a new SME array is loaded, the list of excised actors is changed, or saving output is specified, the selected method must be reselected to perform the analysis with those changes.

The following analysis methods are available. All methods use the actor influence network on the SME survey. For all of the methods except *Degree*, only the symmetrized network is used in which the tie strength of each actor pair is the mean of the two directional tie strengths.

Degree. Calculates degree of each actor in the network. This is useful for assessing actor outgoing and incoming influence. Three types of degree are calculated: (1) Out-Degree - the sum of each actor's outgoing influence weights on the other actors. (2) In-Degree - the sum of all the incoming influence weights on the actor' (3) Symmetrized Degree - the average of the out and in-degrees. The data table lists the degrees for each actor. Plots of the bar charts for each degree measure are generated.

Network Plot (Eigenvecs). Produces a two-dimensional plot of the actor network based on the first two eigenvectors of the network modularity matrix (see M.E.J. Newman, "Finding community structure in networks using the eigenvectors of matrices," *Physical Review E* 74, 036104, 2006). This visualization method is based on the assumption that network structure is driven by an underlying tendency of like-minded actors to preferentially associate (homophily). This is useful for assessing factional structure based on relationships among actors. The eigenvectors are labeled as "network dimensions" in the plots. For each of the two network dimensions, the data table displays the eigenvalue and the actor's name and coordinate value sorted from negative to positive. On the plot, network ties are represented by lines between actors where the thickness is proportional to the tie strength and weak ties have been thresholded.

Note. The sign of an eigenvector is arbitrary, i.e., its negative is still an eigenvector. This implies that the network plot can sometimes appear flipped on one or both of the network dimension axes.

Issue-Network Alignment. Calculates the network dimension (i.e., modularity eigenvector) which best correlates with each issue. This allows for an assessment of how polarizing an issue is by taking into account the extent to which actor positions on an issue align with network structure. It also can be used to identify potential factional realignment issues if there are issues which correlate significantly with subordinate network dimensions.

The data table displays the following analysis results for each issue:

- *Polar.* Polarization, defined as the covariance of actor positions on the issue taken over network ties.
- *Assort.* Assortativity, defined as the correlation of actor positions on the issue taken over ties. It measures homophily on the issue but, unlike polarization, does not take the absolute disagreement spread over the issue into account.
- *NetDim.* Number of the network dimension whose actor coordinate values have the highest magnitude correlation with the actor issue positions.
- *FracDim1.* The ratio of the eigenvalue of the given network dimension to that of Network Dimension 1. Network dimensions are ranked in order of decreasing eigenvalue.
- *p value.* The statistical significance of the correlation.
- *Left, Center, and Right Factions.* Factions are demarcated using the actor coordinate values for the associated network dimension. Actors whose coordinates are less than -0.1, between -0.1 and 0.1, and greater than 0.1 are assigned to the left, center, and right factions respectively.

For each issue, a two-dimensional plot of the network is generated in which the horizontal axis is the network dimension which best correlates with the issue. The vertical axis is either Network Dimension #2 or Network Dimension #1 (if it is not the best eigenvector). On the bottom of the plot, the actor issue positions are displayed, rescaled so that they lie within the range of actor best network dimension coordinates. This allows for the identification of individual actors whose issue positions are substantially misaligned with their network positions. The correlation and significance are also shown.

Note. The sign of the best network dimension for an issue is always defined in this method so that the correlation is positive. Consequently, two issues may share the same best network dimension but the left and right factions may be flipped. The right faction is on the more supportive side of the issue and the left faction is on the more opposed side (although bear in mind that the factions here are defined by network coordinates not issue positions).

Factional Maps - 1D. Generates a plot of actor issue positions, influence, and ties for each issue. This is useful for visually assessing factional structure, identifying key individuals, and anticipating policy outcomes. Issue positions are on the horizontal axis. Influence values are on the vertical axis and taken to be network out-degrees normalized so that the mean influence is one. Network ties are represented by lines between actors where the thickness is proportional to the tie strength and weak ties have been thresholded. The data table displays actor influence values and issue positions.

Factional Map - 2D. Generates a factional map for a selected pair of issues. The issues are chosen from a menu which pops up when the method is selected. Only a single pair of issues can be selected. The horizontal axis corresponds to positions on the first issue, the vertical to the second. Influence is proportional to the actor circle area. Network ties are as in the 1D factional map. The data table displays actor influence and positions on the two issues.

Excising Actors

One or more actors can be excluded from the analysis method calculation and plots by selecting them from the **Excise** menu. The method must be reselected after changing the actors to be excised.

Saving Output

Checking the *Save table/plots* box will save the data table and plots generated in MATLAB® format when an analysis method is performed.

The *File name stem* is the file name under which the data table will be saved and is the stem for the file names of the figures. It defaults to the SME name but can be changed or extended to, for instance, indicate excised actors or other specifics.

The *Directory* is the directory in which files will be saved. It defaults to the current directory.

Checking *Save table in Excel* will also save the data table in .xls format.

Checking *Label plots w dir & date* will place the full file name path and date of the analysis on the bottom of the figure window. This is useful for going back to edit original versions of figures pasted into documents.

Note: Files with same file name already existing in the output directory will be automatically overwritten - no prompt asking whether you wish to do so is given.

Procedure

The basic procedure is as follows:

1. Press **Load SME** and select a SME file.
2. Excise one or more actors using the **Excise** list if desired.
3. If desired, check *Save table/plots* to save the output.
4. Select a method from the **Analysis** menu.

For an example, see Network Analysis Example.

Outcome Simulation

Nonlinear Influence Simulation -1D

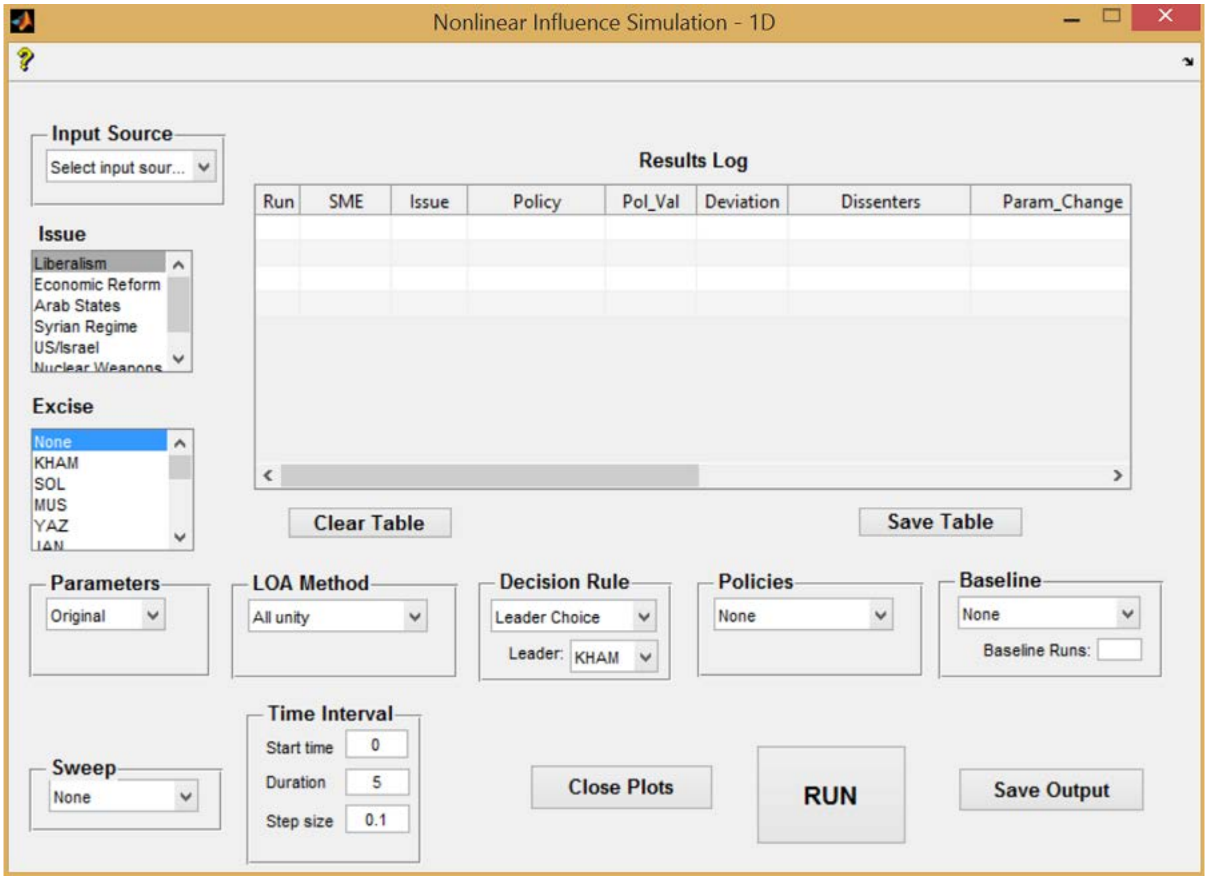
Simulation of nonlinear group decision making model for a single issue.

Nonlinear Influence Simulation - 1D

Simulation of nonlinear group decision making model for a single issue.

Interface

The image below shows the Nonlinear Influence Simulation - 1D interface. It is launched from the PORTEND™ Main Window.



It consists of the following components:

1. **Input Source:** Select one or more SME input arrays.
2. **Issue:** Select an issue to simulate.
3. **Excise:** Exclude selected actors from the simulation.
4. **Parameters:** Change group parameters.
5. **LOA Method:** Select method for calculating latitude of acceptance.
6. **Decision Rule:** Choose the rule for aggregating actor individual policy positions into a group policy.
7. **Policies:** Select how position axis ranges are assigned policy labels.
8. **Baseline:** Select simulation run(s) to serve as baseline reference for comparison.
9. **Sweep:** Conduct simulation over a parameter range.
10. **Time Interval:** Select simulation time settings.
11. **Run:** Execute simulation.
12. **Save Output:** Save plots and simulation data for preceding run.
13. **Close Plots:** Close all open figures generated by this window.
14. **Results Log:** Table showing summary of run results and settings.

The interface requires that Issue Setup, Actor Setup, and Survey Import have been conducted. Policy Setup is needed for assigning policy labels to simulation results.

Loading SME Input Arrays

Selecting *SME Arrays* on **Input Source** pull-down menus opens a window which allows you to select one or more SME input arrays. Simulation runs can be conducted for multiple SMEs at once. The default directory is that specified when importing the SME surveys using the Survey Import function.

Issue Selection

Select the issue to be simulated from the **Issue** menu. Only one issue can be simulated at a time.

Excising Actors

One or more actors can be excluded from the simulation by selecting them from the **Excise** menu. The designated leader cannot be excised if the *Leader Choice* decision rule is selected.

In addition to deliberately investigating the effects of removing actors, the **Excise** menu can be used to enable the simulation of a particular SME input if that SME neglected to contribute sufficient data about one or more actors.

Changing Parameters

The **Parameters** menu can be used to change the following group parameters used in the simulation: actor natural preference, actor status, group coupling scale, and dyadic influence strengths. Selecting *Original* from the pull-down menu will set all group parameters to the values calculated directly from the SME input array(s). Selecting *Change* will open up the Change Group Parameters window in which parameter changes are entered. Then, after a run is executed, the menu will display *Current* to indicate that a changed parameter set is being used for simulations (selecting *Current* performs no actions).

Latitude of Acceptance (LOA) Calculation

The **LOA Method** menu is used to select the manner of LOA determination via one of the following methods:

- ***All unity.*** LOA is set to one for all actors.
- ***Specify constant.*** Specify non-unity LOA for all actors (must be >0)
- ***SME deviation.*** Calculates an actor's LOA as standard deviation of natural preferences for selected issue taken over SMEs. A window is opened for selecting SME input arrays to be used in the standard deviation calculation. Requires at least two SMEs (including composite SMEs is inadvisable). LOAs less than the minimum value of 0.1 are set to 0.1. Note that the same LOA values are used for all the SME arrays chosen under **Input Source** for simulation. If a change is made to the **Input Source** SME arrays, a prompt will appear stating that you may wish also to reselect the SME arrays used for calculating the LOA (but there is no need to do so).
- ***Statement deviation.*** Calculates an actor's LOA for an issue as the standard deviation of the actor's responses to the survey attitude statements corresponding to that issue. It is calculated separately for each SME. LOAs less than the minimum value of 0.1 are set to 0.1.
- ***Dyadic similarity.*** Calculates a separate LOA for each directed dyad using the assumption that an actor will have larger LOAs for actors who have similar natural preferences across issues. It is calculated for each SME independently does not vary by issue. The minimum LOA value is 0.5 and the maximum is 1.5.

For more detail on the above LOA calculation methods, see the appendix on Parameter Calculation for Group Decision Making Model.

Decision Rule Selection

The decision rule determines how the actor positions in the simulation are aggregated to form a group policy. It is primarily of importance for determining the final policy but it is calculated by the simulation for all time steps. The following decision rules can be selected:

- ***Leader Choice.*** The group policy is the position of the actor chosen in the *Leader* pull-down menu.
- ***Weighted Majority.*** The group policy is the position which receives the most status/salience-weighted support. An actor's maximum support level is the (normalized) product of status and issue salience. An actor provides maximum support to a candidate policy that is the same as his current position but the support decreases as the distance between the candidate policy and his current position grows. The functional form of the distance fall-off is a Gaussian whose width (sigma) is given by the actor's LOA.

Note: On the simulation plots, the policy is shown by a solid black curve connecting an open black square at the start time with a solid black square at the end time. If *Leader Choice* is in effect, the policy line will be overlaid on the leader's curve.

Policy Labeling

The method by which a qualitative policy name can be assigned to the numerical policy value obtained from the simulation is selected using the **Policies** menu. The following options are available:

- ***None.*** No policy labeling.
- ***SME-Based.*** Policy labels are assigned to position intervals based on selected attitude statements in the SME survey. Intervals are calculated separately for each SME array.
- ***User-Specified.*** User-specified policy intervals are used for all SME arrays.

The *SME-Based* and *User-Specified* options require that Policy Setup has been performed.

Baseline Comparison

When a parameter or setting change is made, **Baseline** can be used to compare the resulting actor final positions with those of a baseline case, such as the original group parameters. The baseline case must first be run and then *Set to Current Output* selected. The run number (or numbers if multiple SME arrays are being simulated at once) of the baseline case is shown in the *Baseline Runs* box. The comparison plot shows the baseline final actor positions and policy at the bottom and their new values at the top. Select *None* if you do not wish to generate the comparison plot.

Notes

1. Baseline comparison plots can only be generated for the same SME array, not between different SMEs.
2. If baseline runs for mulitple SMEs were set and then further simulations are conducted with only a subset of those SMEs, comparison plots will continue to be generated for the remaining SMEs. However, baseline plotting will cease if new SMEs are added under **Input Source**.

3. Excising actors requires that the baseline case be rerun with the reduced actor set.
4. Baseline comparison cannot be done for parameter sweeps (it would be effectively redundant).

Parameter Sweeps

The **Sweep** menu allows for simulations to be conducted over a range of values for a parameter and plots the behavior of model variables vs the parameter value. The following options are available:

- ***None.*** No parameter sweep.
- ***Nat. Pref. Shift.*** The shift in the natural preference from the original SME value of one or more actors is swept through a given range (the same for all actors). A window opens which allows you to select the actors and the start, end, and step size of the range. A shift value of 0 corresponds to the original SME natural preference value for an actor.
- ***Status Multiple.*** This sweeps the value which multiplies actor influence in the influence network and status used in the *Weighed Majority* decision rule. All actors are swept through the same multiple range. A window opens which allows you to select the actors and the start, end, and step size of the range. A multiple of 1 corresponds to the original SME influence network and status. Status multiples must be greater than 0.
- ***Coupling Scale.*** The coupling scale, a measure of group cohesion, is swept. The values correspond directly to the coupling scale value (and not relative to the original SME value as in the preceding options). Changing the coupling scale affects the strength of ties between actors and commitments. A window opens which allows you to select the start, end, and step size of the range. Coupling scale values can line in the range of 0 to 1 (inclusive).

Conducting a parameter sweep produces figures plotting the following variables vs. the parameter sweep range: (1) Final policy; (2) Actor final positions (and policy); (3) Standard deviation of actor final positions (blue line) and actor concurrence intervals. The concurrence interval is the range of parameter values over which an actor concurs with the policy with concurrence holding when the policy is less than one LOA from the actor's final position. Concurrence intervals are shown as double-arrowed lines with the actor's abbreviation above. An actor who does not concur anywhere within the sweep range is placed at the sides of the plot (the algorithm attempts to put them on the side indicating which direction the parameter would have to move in to gain their concurrence - difficult when the behavior is nonmonotonic). Policy labels and boundaries are shown on the plots if the appropriate **Policies** selection is made.

Notes

1. Parameter sweeps can be conducted in conjunction with point parameter changes made using the Change Group Parameters window. If there is a conflict - the same parameter has a point change and is being swept - the sweep overrides the point change.
2. If the difference between the start and end of the range is not an integer multiple of the step size, then the step size is rounded down to the nearest value yielding an integer multiple. The sign of the step size must be consistent with the start and end values, i.e., if the end value is less than the start, the step must be negative.

Setting Simulation Time Interval

The start time, duration, and step size of the simulated time can be changed using the **Time Interval** panel. Simulated time is in arbitrary units but the duration can affect whether actors reach their equilibrium positions by the end of the simulation. Decreasing the step size allows for more finely resolved trajectories but will increase the (actual) run time of the simulation. (Changing the start time will be useful when the capability to use prior run outputs as initial conditions for new runs is implemented).

Executing Simulation

After the desired settings have been made, pressing **RUN** will execute the simulation. Plots are generated and results and settings summarized in the **Results Table**.

Saving Output

Plots and data generated by the run can be saved by pressing the **Save Output** button. A window appears in which the following specifications can be made:

- ***Core File Label.*** Serves as a base to which output specific suffixes can be added. The default value is the abbreviation of the simulated issue for a single parameter set (non-sweep) run. For a parameter sweep, the default value is the issue abbreviation with the parameter being swept appended. If parameter changes or actor excisions have been made, you should change the core file label appropriately. It must start with a letter and contain only letters, numbers, and underscores.
- ***Output Base Directory.*** This is the directory in which the output files are saved directly or in SME subdirectories. If the file does not exist, you will be prompted if you wish to create it.
- ***Prepend SME Identifier.*** If checked, then the SME name will be placed in front of the *Core File Label*.
- ***Create SME Subdirectories.*** If checked, output files will be saved in a subdirectory of the *Output Base Directory* corresponding to each SME in the run. You will not be prompted to create the SME subdirectories if they do not exist.
- ***Date, Directory Labels.*** If checked, places the full file name path and date of the analysis on the bottom of the figure window. This is useful for going back to edit original versions of figures pasted into documents.

For a single parameter set run, a data file is saved whose name is `CoreName.mat` where `CoreName` is the *Core File Label*. If *Prepend SME Identifier* is chosen, then the file name will be `SMEName_CoreName.mat` where `SMEName` is the SME identifier. The data file contains a structure called InpArg which contains the input specifications of the run and a structure called OutData which contains various outputs including the actor position trajectories over time. The plot of the actor trajectories is saved in a .fig file with the suffix "_traj" appended, e.g, `CoreName_traj.fig`.

For a parameter sweep, the data file is saved as for a single parameter run. Actor trajectories are saved for every parameter value in the sweep range. The plots are given the following suffixes: (1) final policy - "_pol"; (2) actor final positions - "_pos"; (3) Standard deviation and concurrence intervals - "_dev".

Notes

1. Only the output that was generated by the most recent press of the **RUN** button can be saved. Plot windows must be open in order to be saved. The data from a run, however, can be saved even if the plots have been closed.
2. If multiple SME arrays are simulated at once, one of either *Prepend SME Identifier* or *Create SME Subdirectories* must be checked (both can be checked). Otherwise, the different SME outputs would be written to the same file.
3. If a file with the same name already exists in a directory, it will automatically be overwritten - no prompt will be given.

Closing Plots

All open plot windows generated by the simulation runs are closed when the **Close Plots** button is pressed. In addition, all plot windows are closed when the simulation window itself is closed.

Results Log

The **Results Log** summarizes selected run results and settings. It provides a convenient record of how simulation results vary by SME and settings and allows users to enter brief notes about each run. The following columns are present:

1. *Run.* Run number. When multiple SMEs are being simulated simultaneously, each SME is given a separate run number.
2. *SME.* SME name.
3. *Issue.* Issue abbreviation.
4. *Policy.* Label of final group policy. Not present for sweeps or if policy labeling is not in use.
5. *Pol Val.* Numerical value of the final group policy. Not present for sweeps.
6. *Deviation.* Standard deviation of actor final positions. Not present for sweeps.
7. *Dissenters.* List of actors who dissent from group policy. An actor dissents when the policy is more than one LOA distant from the actor's final position. Not present for sweeps.
8. *Param Change.* List of all point parameter changes. The following abbreviations are used: "np" - natural preference, "st" - status multiple, "cs" - coupling scale, "dy" - dyadic influence.
9. *Excise.* List of excised actors.
10. *Dec Rule.* Decision rule. The designated leader is listed if *Leader Choice* is the decision rule.
11. *Sweep.* Type and range of swept parameter.
12. *Saved File.* Name of file if saved. A shortened folder path is used.
13. *Notes.* User annotation.

Clear Table clears all entries from the table. ***Save Table*** allows the table to be saved in .mat, .xls(x), or .csv formats.

Procedure

The basic procedure is as follows:

1. From the **Input Source** menu, select *SME Arrays*, then select one or more SME files.
2. Select an issue from the **Issue** menu.
3. Choose options as desired. (**Baseline** can only be chosen after a run.)
4. Change parameters using the **Parameters** menu if desired.
5. If desired, set a parameter sweep using the **Sweep** menu.

6. Press **RUN**.
7. Save the ouput of the preceding (not subsequent) run with the **Save Output** button.

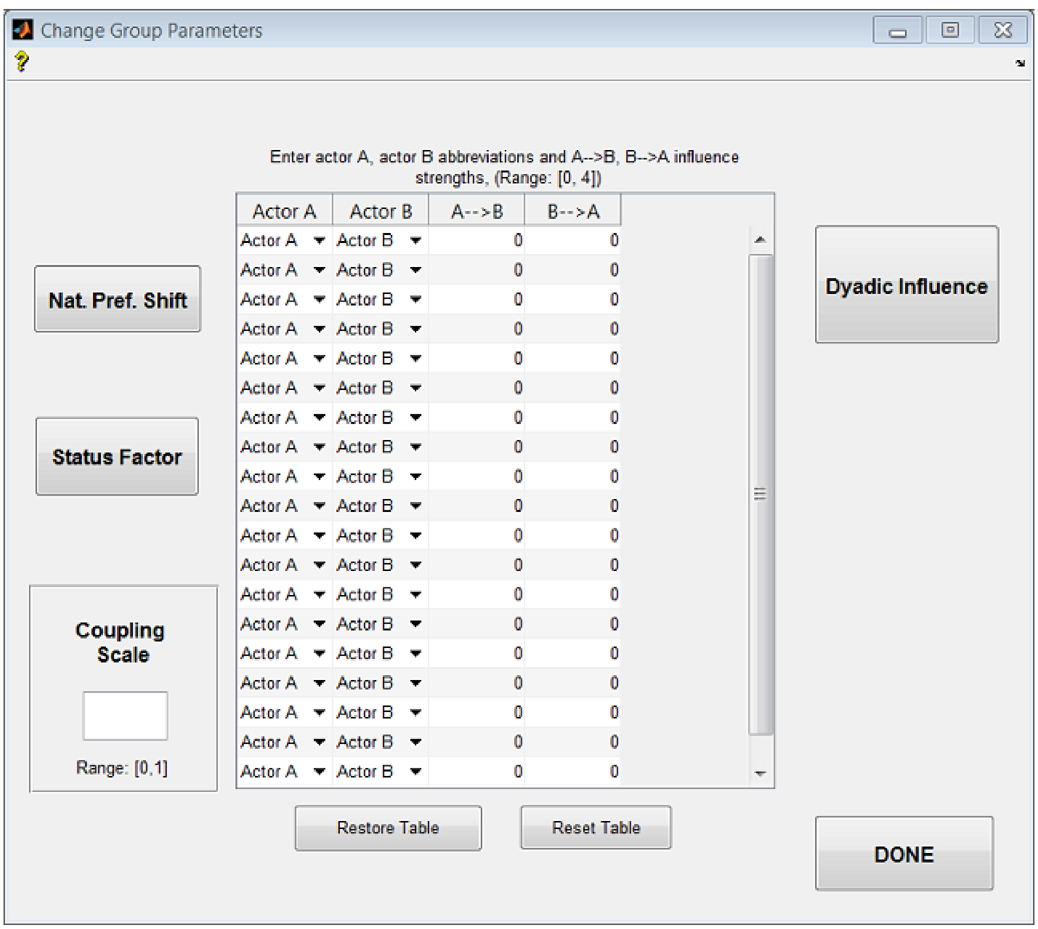
For an example, see Nonlinear Influence Simulation (1D) Example.

Change Group Parameters

Change group parameter values used in simulation.

Interface

The image below shows the Change Group Parameters interface (for *Dyadic Influence* parameters). It is launched from the PORTEND™ Nonlinear Influence Simulation by selecting *Change* in the *Parameters* menu.



It consists of the following main components:

1. **Parameter Table:** Enter values for actors for parameter type to be changed.
2. **Nat. Pref. Shift:** Shift actor natural preferences from original values.
3. **Status Factor:** Multiply status and influence of actors relative to original value.
4. **Dyadic Influence:** Enter new directed influence strengths for actor dyads.
5. **Coupling Scale:** Enter new value for coupling scale.

Pressing **DONE** sets the parameter changes for use in the simulation.

The parameter changes that can be effected with this interface are "point parameter" changes in which a given parameter is given a single new value. To sweep over a range of parameter values, use the Sweep menu of the Nonlinear Influence Simuation.

Natural Preference Shift

The natural preference shift is the amount by which an actor's natural preference will be shifted relative to the original SME value. Pressing **Nat. Pref. Shift** presents a list of actors along the rows and a column in which to enter the natural preference shift amount for each actor. A natural preference shift of 0 makes no changes.

Status Factor

The status factor can be used to represent increases or decreases in an actor's status and influence on other actors. Status is used in the Weighted Majority decision rule. The status factor multiplies the actor's original status as derived from the SME survey. The status factor also multiplies the actor's influence strength as a source on the other actors which will impact the coupling strengths and commitments in the simulation.

Pressing **Status Factor** presents a list of actors along rows and a column in which to enter the status factor. Status factors must be larger than 0. A status factor of 1 makes no changes.

Dyadic Influence

The influence network between actors can be changed on a pairwise basis by pressing **Dyadic Influence**. This will change the coupling strengths and commitments in the simulation. Four columns are displayed in the parameter table: use the ***Actor A*** and ***Actor B*** pull-down menus to set the dyad members; use ***A-->B*** to enter the influence strength of Actor A on Actor B and similarly for ***B-->A***. Influence strengths must lie in the range from 0 to 4 (inclusive). A maximum of 20 dyads can be changed.

If you wish to remove a dyad, select *Actor A* and *Actor B* from the pull-down menus in the appropriate row.

Coupling Scale

The coupling scale is a measure of group cohesion. The SME-derived value is determined by the influence network and susceptibility. Enter the coupling scale in the box in the **Coupling Scale** panel. Range: 0-1 inclusive. The coupling scale affects the coupling strengths and commitments.

Restoring/Resetting Parameter Table

Restore Table sets the values in the parameter table to those that were set the last time **DONE** was pressed. This can be used to reverse edits to a parameter type.

Reset Table sets the values back to the default settings, which leave the parameters unchanged from the original SME values.

Notes

1. **Nat. Pref. Shift** and **Status Factor** make changes relative to the original values derived from the SME data and hence the new natural preference or status will in general be different for different SMEs. For **Dyadic Influence** and **Coupling Scale**, the user directly enters the new parameter values and so they will be the same for all SMEs.
2. Actors who are on the *Excise* list in the simulation will still appear in the **Change Group Parameters** interface. Any changes made to the parameters of excised actors will be ignored in the simulation.
3. For information about parameter calculation, see the Parameter Calculation for Group Decision Making Model appendix.

Examples

Issue Analysis Example

Conducting issue analysis steps using Iran example case.

Network Analysis Example

Conducting network analysis steps using Iran example case.

Nonlinear Influence Simulation (1D) Example

Conducting 1D nonlinear influence simulation using Iran example case.

Issue Analysis Example

Conducting issue analysis using an example case.

Example Case

The case used for this example is *Iran1* and is already set up. It consists of 15 Iranian leadership actors from late 2013 shown in the table below. Seven issues are included: Liberalism (LIB), Economic Reform (ECON), Arab States (ARAB), Syrian Regime (SYR) US/Israel (USISR), Nuclear Weapons (NUKE), and IRGC Influence (IRGC). It contains two individual SME surveys and one composite SME (absolute method of aggregation).

Actor (Abbr.)	Role/Notes
Ali Hoseini Khamenei (KHAM)	The supreme leader, the highest political and religious authority in the Islamic Republic of Iran.
Qasem Soleimani (SOL)	Commander of the Quds Force, a unit of the Islamic Revolutionary Guard Corps (IRGC). He is seen as a possible future commander of the IRGC.
Mir Hossein Musavi (MUS)	Prime Minister of Iran from 1981 to 1989. In 2009 he was the reform candidate for president, around whom the Green Movement coalesced. He has been under house arrest since February 2011.
Mohammad Taqi Mesbah Yazdi (YAZ)	A hardline cleric and politician. He is a member of Iran's Assembly of Experts and is seen as the most conservative cleric in Iran.
Ahmad Janati (JAN)	A hardline cleric and chairman of the Guardian Council.
Asadollah Asgaroladi (ASG)	An important businessman with interests in exports, banking, real estate and healthcare. President of several of Iran's international Chambers of Commerce.
Ali Akbar Hashemi-Rafsanjani (RAF)	Served as president of Iran from 1989 to 1997 and is currently the chairman of the Expediency Council.
Ali Ardeshir Larijani (LAR)	Current chairman of the Iranian Parliament and former secretary of Iran's Supreme National Security Council.
Yousef Sanei (SAN)	An Iranian scholar and Islamic theologian and philosopher. He has been known to call for radical reforms within the Iranian political system. He serves as a Grand Marja of Shia Islam.
Mohammad Baqr Qalibaf (QAL)	The current mayor of Tehran .
Yahya Rahim Safavi (SAF)	An Iranian military commander and former Chief Commander of the IRGC.
Mahmud Ahmadinejad (AHM)	The former president of Iran.
Seyyed Mohammad Khatami (KHAT)	President of Iran from 1997 to 2005. One of Iran's most prominent reformers.
Saeed Jalili (JAL)	Secretary of Iran's Supreme National Security Council, the equivalent of the U.S. National Security Council.
Hassan Rouhani (ROU)	The current president of Iran.

Loading the Case

If not already loaded, load the example case as follows:

1. From the **Cases** menu of the PORTEND™ main window, select *Load Case*.
2. Select *Iran1* from the list of cases and press *OK*.

The **Current Case** box should read *Iran1*.

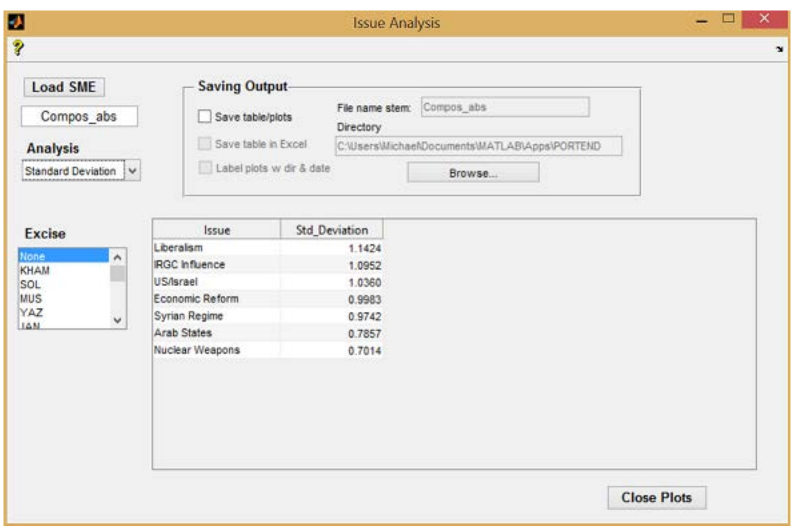
Issue Analysis Steps

1. From the **Structure** menu of the PORTEND™ main window, select *Issues* which launches the Issue Analysis interface.
2. Click **Load SME**. A file selection box should open in the directory `...\PORTEND\demos\Iran1\input`. Select `Compos_abs_inp`, a composite SME, and click *Open*.
3. Analysis methods are listed in the **Analysis** pull-down menu. They can be performed in any order.
4. If you wish to save the output, check *Save table/plots* and enter the file name stem and the directory where you wish to save the output. Then select the desired analysis method. There are options for saving the data table in Excel format and labeling the plots with the directory where they are saved and the date generated.
5. One or multiple actors can be removed by selecting them in the **Excise** menu.

The output of the analysis methods are described in the following sections.

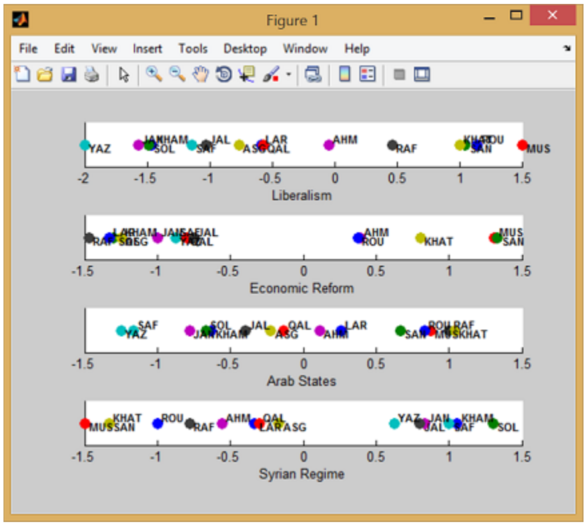
Standard Deviation

Select *Standard Deviation*. The data table will display the names of the issues and the standard deviation of the actor positions on each as shown below. The issues are ranked in descending order. The standard deviation can serve as a measure of how contentious the issue is based on the spread of actor positions. Liberalism is seen as the most contentious issue while Nuclear Weapons is the least. However, the standard deviation does not take the network into account and therefore does not address the extent to which network structure can heighten or mitigate the issue disagreement (see *Issue-Network Alignment* in Network Analysis Example).



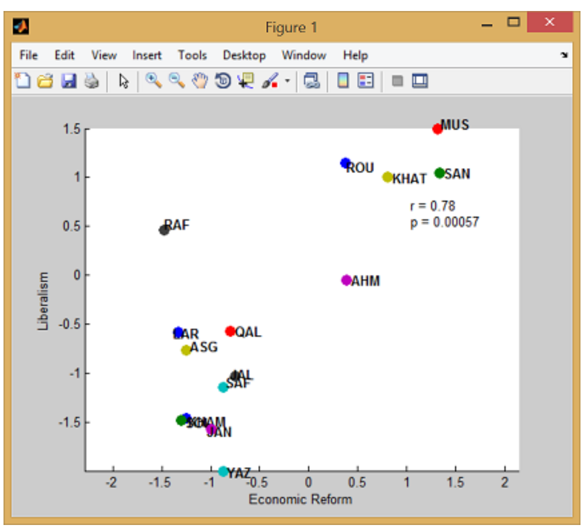
Issue Plots

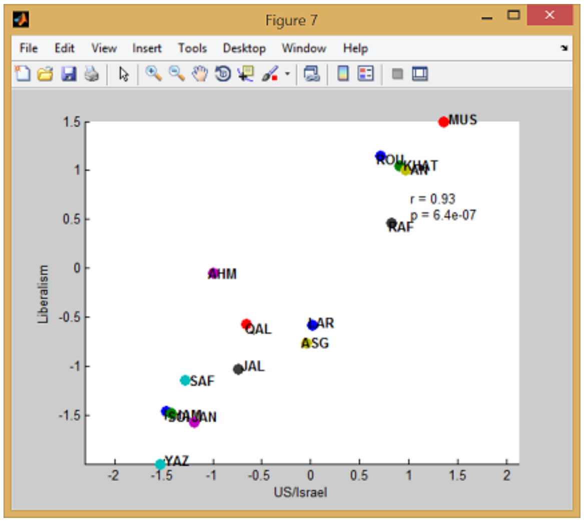
Select *Issue Plots*. Two figures will appear showing the actor postions on each of the seven issues. The figure with the first four issues is shown below. The data table shows the numerical actor positions for each issue. KHAM, the Supreme Leader, is usually found toward the extreme end of the spectrum, aligning with other conservatives like SOL, SAF and JAN. A core reform bloc of ROU (the president), KHAT, MUS, and SAN is also present across the issues. Note that RAF is usually aligned with them except on the Economic Reform issue. LAR, QAL, and ASG form a centrist bloc with the exception of Economic Reform.



Cross-Correlation

Select *Cross-Correlation*. For each pair of issues, a figure will be generated which plots the actor positions on one issue vs. the other. The data table shows two tables: (1) the correlation values for each pair of issues; (2) the statistical significance of each correlation. A high positive correlation indicates that actors tend to have similar positions on both issues - if they favor one, they favor the other - whereas a high negative correlation indicates a tendency to favor one issue and oppose the other. The figures below show the correlation of the Liberalism issue with Economic Reform and US/Israel. While both have high magnitude correlations, there is significantly more spread on the Economic Reform issue with some actors - RAF and AHM - aligning with different factions on Economics than they do for Liberalism.

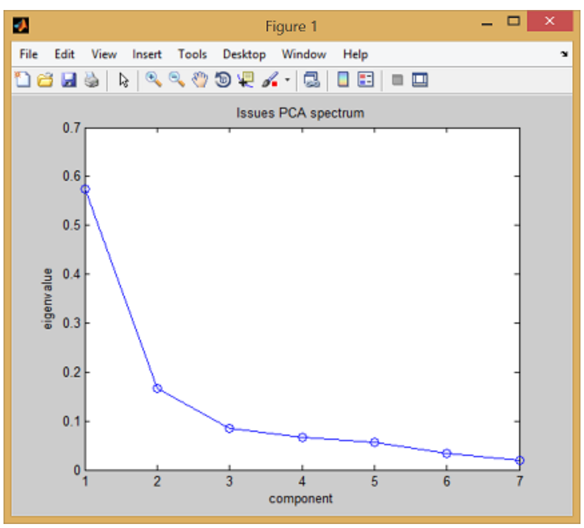




Principal Component Analysis

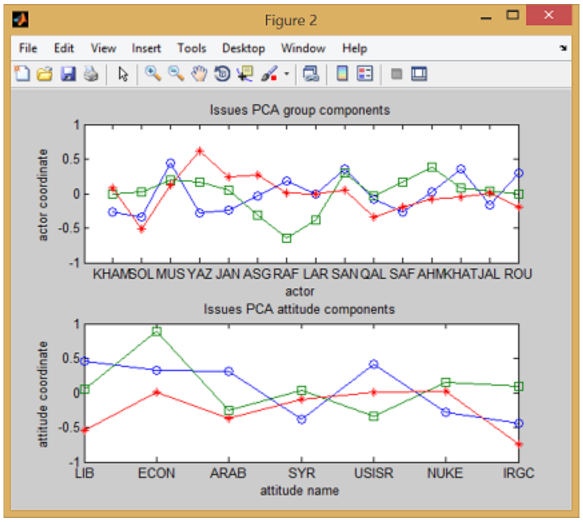
Select *PCA*. Four figures and a table are generated:

1. ***PCA Spectrum.*** This shows the eigenvalue for each Principal Component (PC), normalized so that the sum is one. This is equal to the fraction of the variance carried by each PC. The first PC has an eigenvalue of 0.57, more than half the variance and much larger than the second PC, indicating that the system is substantially one-dimensional: there is a dominant split between conservatives and reformers that is present across issues.

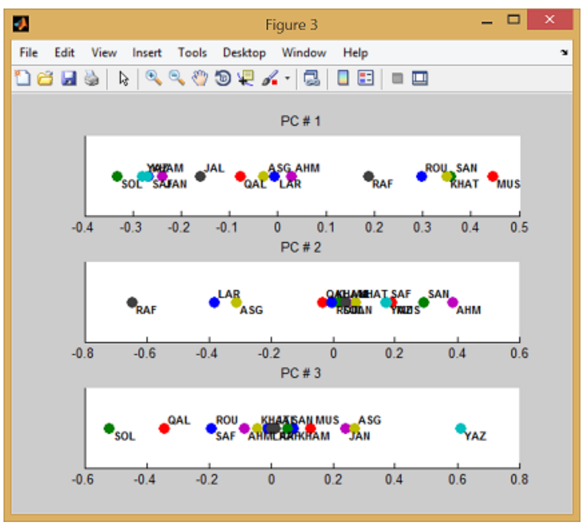


2. ***Actor and Issue Principal Components.*** The top panel shows the first three PCs (blue, green, red) respectively for the actors and the bottom panel shows the same PCs for the issues. The magnitudes, rather than the signs, indicate which actors or issues are important for a given PC. PC 1 shows comparable magnitudes across issues, yielding its interpretation as the dominant factional split. PC 2 is dominated by the ECON issue indicating that this issue causes a significant change from the dominant

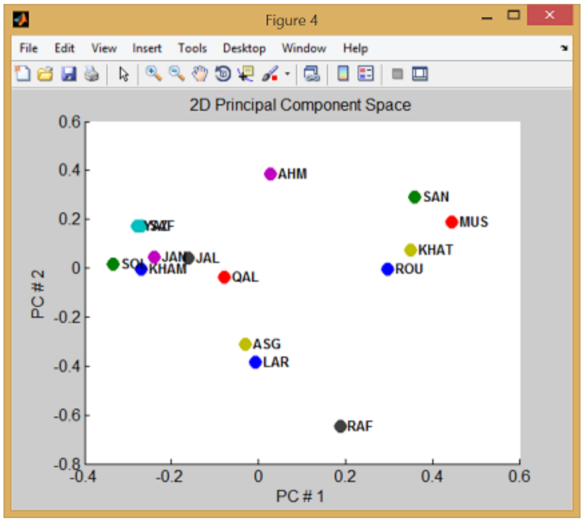
split. The actor plot for PC 2 shows that RAF has an outsized value reflecting his strong opposition to this issue.



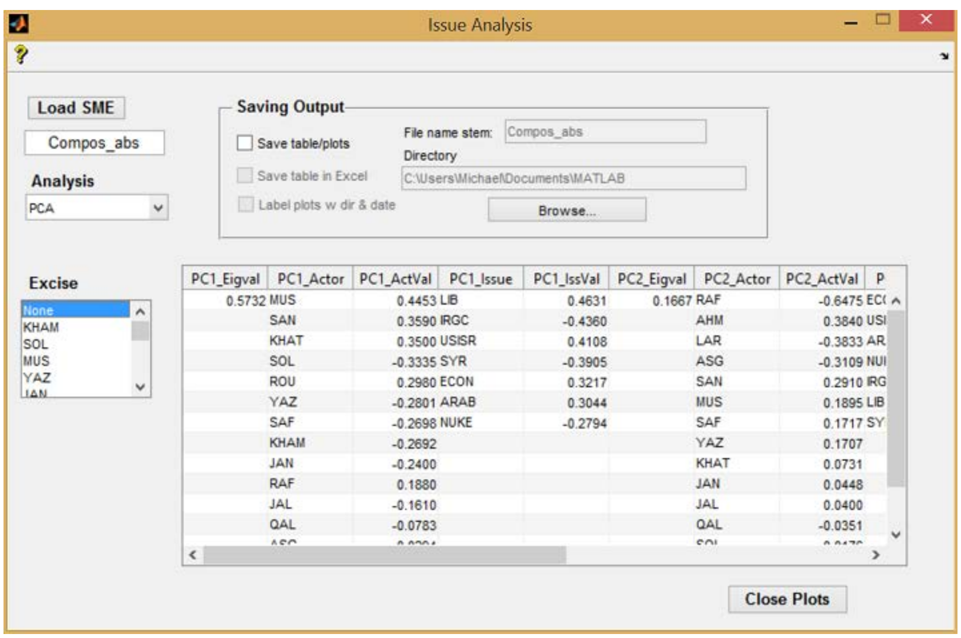
3. ***Actor Principal Component Axes.*** Actor coordinates for the first three PCs plotted on a one-dimensional axis as in the issue plots above. PC 1 shows the alignment of conservatives on the left and reformers on the right and a centrist bloc of LAR, QAL, ASG, and AHM. PC 2 shows the departure of the positions of RAF and AHM in particular from that of PC 1.



4. ***2-D PC plot.*** The first two PCs are plotted against each other. Note that the PCs have not been scaled by their eigenvalues so distances on the plot are not true distances. Otherwise, the vertical direction would appear more compressed.



5. ***Data Table.*** For each of the first three PCs, the data table lists: (1) the eigenvalue; (2) the actors in descending order of the magnitude of their coordinate values for that PC; (3) the coordinate value for each actor; (4); the issues in descending order of the magnitude of their coordinate values for that PC; (5) the coordinate value for each issue. The actors or issues with the highest magnitudes are the most important for that PC. To obtain which side, positive or negative, of a given issue that a given actor is on for a particular PC, look at the product of his coordinate value and the issue coordinate value. For example, KHAM's side on the Nuclear Weapons issue in PC1 is obtained from the sign of the product of his coordinate (-0.2692) and the NUKE issue (-0.2794) which yields a positive sign indicating that KHAM is on the pro-Nuclear Weapons side (Note that since the mean is subtracted for PCA, technically we can only say that he is on the positive side relative to the mean).



Network Analysis Example

Conducting network analysis using an example case.

Loading the Case

The case used here is the Iranian leadership case (see the Issue Analysis Example for a brief description).

If not already loaded, load the example case as follows:

1. From the **Cases** menu of the PORTEND™ main window, select *Load Case*.
2. Select *Iran1* from the list of cases and press *OK*.

The **Current Case** box should read *Iran1*.

Network Analysis Steps

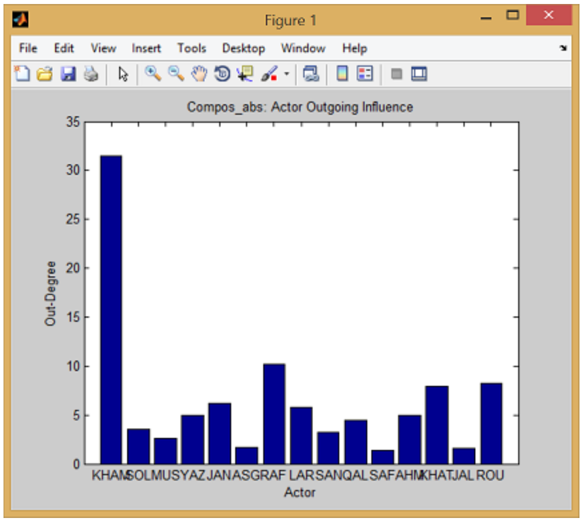
1. From the **Structure** menu of the PORTEND™ main window, select *Network* which launches the Network Analysis interface.
2. Click **Load SME**. A file selection box should open in the directory `...\PORTEND\demos\Iran1\input`. Select `Compos_abs_inp`, a composite SME, and click *Open*.
3. Analysis methods are listed in the **Analysis** pull-down menu. They can be performed in any order.
4. If you wish to save the output, check *Save table/plots* and enter the file name stem and the directory where you wish to save the output. Then select the desired analysis method. There are options for saving the data table in Excel format and labeling the plots with the directory where they are saved and the date generated.
5. One or multiple actors can be removed by selecting them in the **Excise** menu.

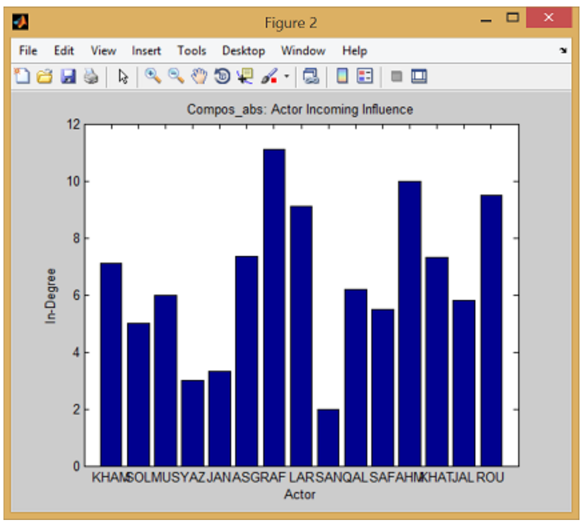
The output of the analysis methods are described in the following sections.

Degree

Select *Degree*. Bar plots and columns in the data table are generated for three types of degree: (1) Out-Degree - a measure of the actor's influence on others; (2) In-Degree - a measure of the influence of the rest of the group on the actor; (3) Symmetrized Degree - the average of the out and in-degrees.

The first two plots are shown below. We see the outsized influence of KHAM, the supreme leader by his out-degree. The great disparity between his out-degree and in-degree indicate that his position is not likely to change much. RAF is seen as having the second highest out-degree and highest in-degree. The latter, combined with his position as a centrist reformer in the dominant factional split (see the PCA plots in Issue Analysis Example), could make him a swing player depending on factional power.

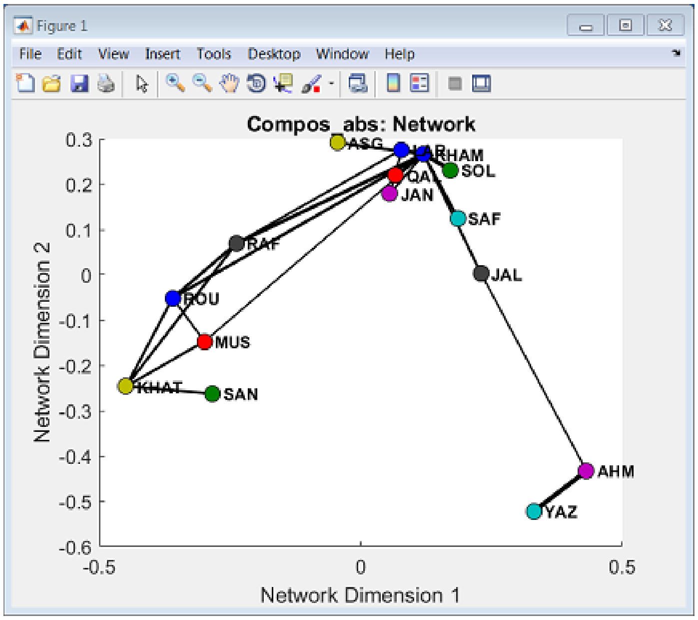




Network Plot (Eigenvecs)

Select *Network Plot (Eigenvecs)*. A figure is generated in which the first two eigenvectors of the network modularity matrix, labeled as network dimensions, are plotted against each other. The thickness of the line connecting two actors is proportional to the strength of the (symmetrized) tie between them (with weak ties thresholded out). The data table displays for each network dimension: (1) the eigenvalue; (2) the actors listed in ascending order - from negative to positive - of their components in the network dimension; (3) the actor components in the network dimension.

Network Dimension 1, shown on the horizontal axis, captures the split between the reformers on the lefthand side and the conservatives on the right. Note, however, that only network information is used in this plot, the integration of network and issue information is shown in the next section. KHAM (blue dot toward the center-top of the plot) is towards the center of Network Dimension 1 in contrast to his more extreme position in the dominant issue split in the Issue Analysis Example. Network Dimension 2, on the vertical axis, represents different network structure (which can be related to the ECON issue as discussed below) with AHM and YAZ at the bottom end, forming a distinct subfaction.



Issue-Network Alignment

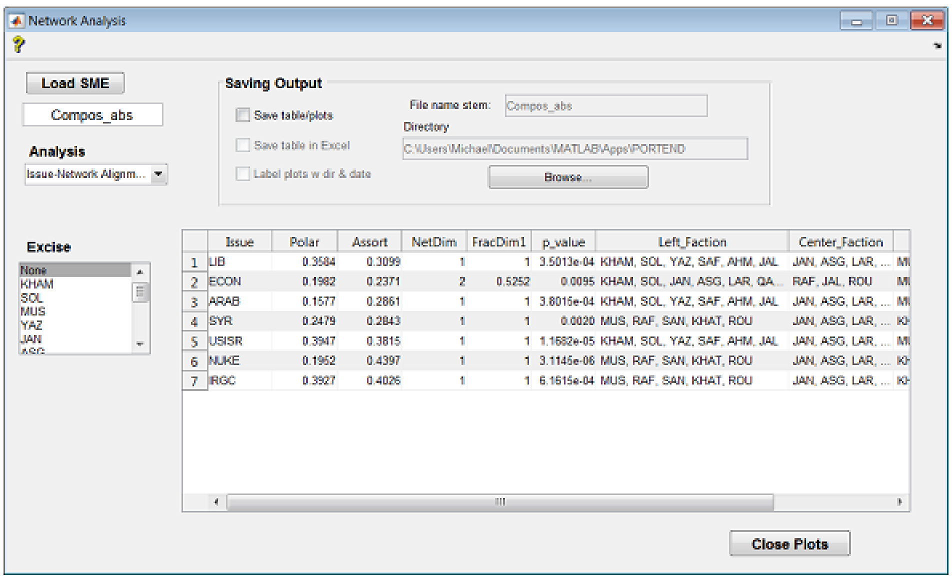
Select *Issue-Network Alignment*. This methods integrates issue data and influence network data. The purpose is to gauge the extent to which divides over issues align with network divides. The data table shows a number of different metrics. Seven plots are generated, one for each issue.

Data Table. The elements of the data table are as follows:

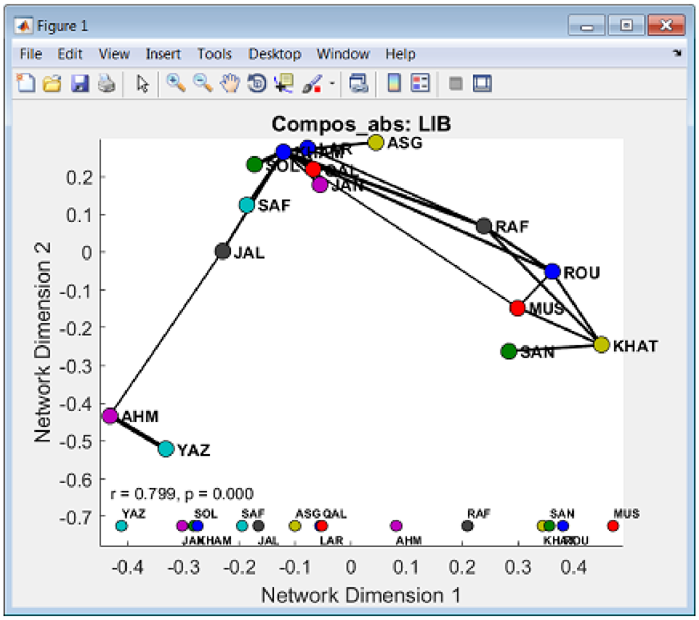
- *Polar, Assort:* These first two columns measure the tendency of actors to have stronger ties with those who have similar positions on the issue. *Polar* is the polarization, the covariance of actor issue positions taken over network ties. *Assort* is the assortativity, the correlation of actor issue positions taken over ties. *Polar* is, as the name implies, a better overall measure of the simultaneous polarization along issue and network structure. It takes the absolute level of disagreement on the issue into account whereas *Assort*, as a correlation, normalizes that away. The USISR issue is seen to have the highest polarization whereas it was only the third highest in standard deviation implying that the USISR issue disagreement reinforces network divides more so than LIB which had the highest standard deviation. The NUKE issue has the highest assortativity (0.4397) whereas its polarization is second lowest (0.1952). The difference is due to the relatively low level of disagreement on NUKE as seen by its low standard deviation.
- *NetDim, FracDim1:* Correlations of the actor issue positions are taken with the actor coordinates for each network dimension (eigenvector). Eigenvectors are ranked in descending order of their eigenvalues. *NetDim* is the number of the network dimension that has the best correlation with the actor issue positions (the sign of the network dimension is chosen so that the correlation is always positive). *FracDim1* is the ratio of Network Dimension *NetDim*'s eigenvalue to that of Network Dimension 1. Six of the issues are seen to correlate best with the first network dimension indicating that they align with the dominant split in the network. However, ECON

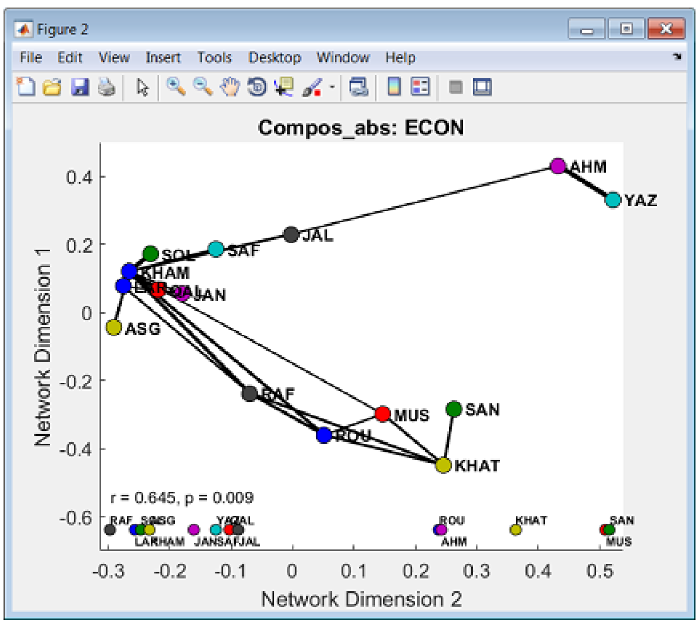
best correlates with the second network dimension indicating that it aligns with subsidiary structure in the network and suggesting the potential for factional realignment if the salience of ECON is raised, leading to the formation of new alliances between actors.

- *p-value:* The statistical significance of the correlation between Network Dimension *NetDim* and the actor issue positions, i.e., the probability of the null hypothesis that the observed correlation or better could have been obtained by chance. Observe that all the p-values are highly significant.
- *Left/Center/Right Factions:* The left faction consists of actors whose Network Dimension *NetDim* coordinates are less than -0.1; center is between -0.1 and 0.1; and right is greater than 0.1. Note that, although issue information was used to determine the best network dimension, it is not used in determining factions. Consequently, all issues with the same *NetDim* will have the same members in each of the three factions (although the left and right factions may flip depending on what the positive sign of the issue signifies). Only ECON has a different factional compositions indicating potential realignment in going from Network Dimension 1 to 2.



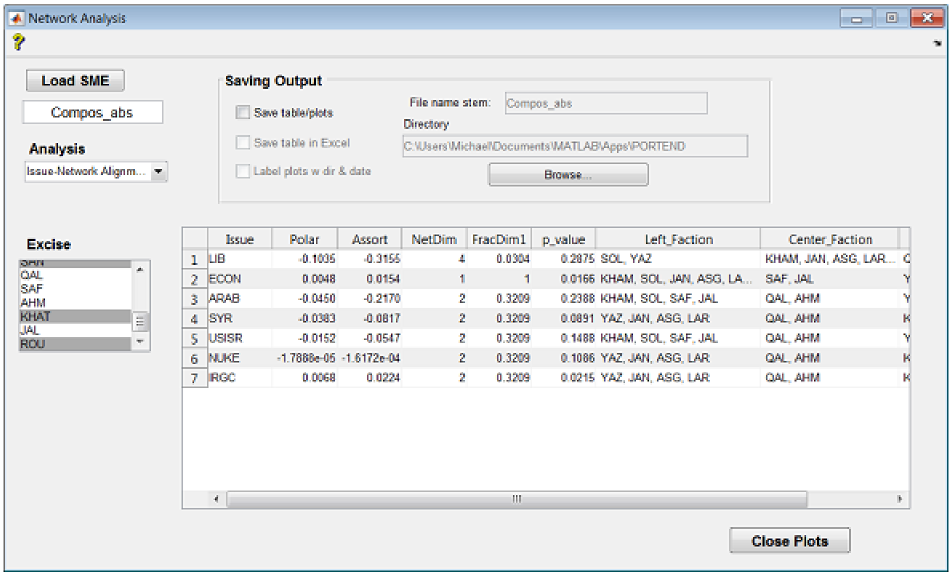
Alignment Plots: For each issue, the network is plotted with the actor coordinates coming from two network dimensions: the x-axis is that of Network Dimension *NetDim* and the y-axis is either Network Dimension 2 if *NetDim* = 1 or Network Dimension 1 otherwise. The bottom of the plot shows the actor issue positions rescaled to fit in the x-axis range. In addition, the correlation r and p-value p are shown. The first plot below is for the LIB issue which aligns with Network Dimension 1. Note however that the correlation is not perfect and some actors have significantly different eigenvector coordinates and issue positions, AHM for instance. For the ECON plot, Network Dimension 2 appears on the x-axis as that dimension is best correlated.





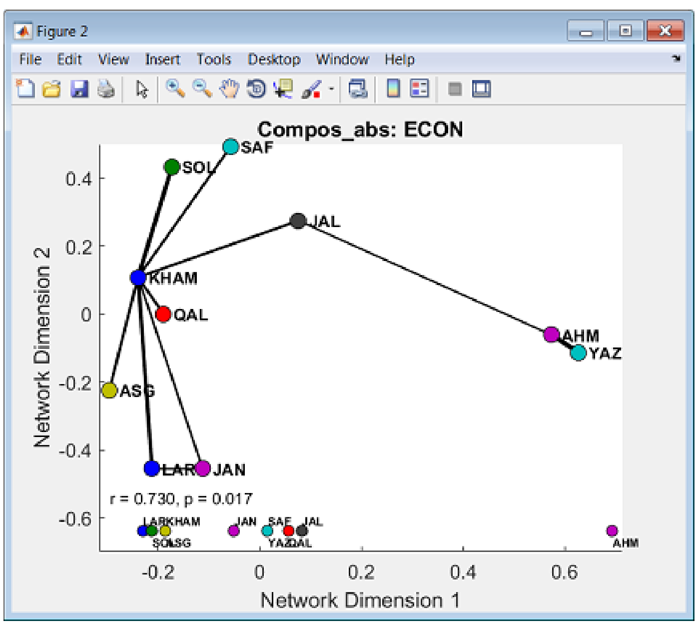
Conservatives Only Example. The Issue-Network Alignment analysis can also illuminate the structure of subsets of the actors. In the figures below, the reformers - ROU, KHAT, MUS, SAN, and RAF have been removed.

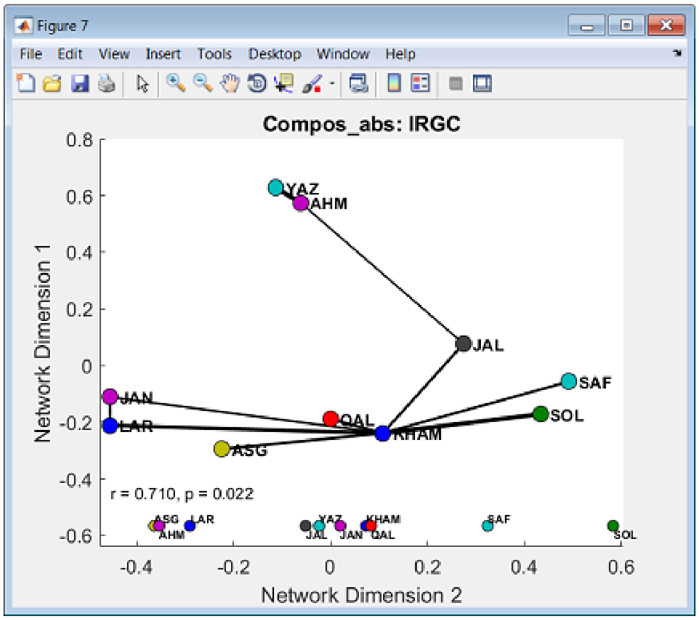
The polarization and assortativity values are for the most part much smaller than for the full actor set indicating narrower issue spreads and less issue-based sorting. Note that negative values technically signify that actors form ties disassortatively so that they tend to have stronger ties with more distant others. However, with the possible exception of LIB's assortativity, the negative values in the table are too small to be statistically significant.



	Issue	Polar	Assort	NetDim	FracDim1	p_value	Left_Faction	Center_Faction
1	LIB	-0.1035	-0.3155	4	0.0304	0.2875	SOL, YAZ	KHAM, JAN, ASG, LAR...
2	ECON	0.0048	0.0154	1	1	0.0166	KHAM, SOL, JAN, ASG, LA...	SAF, JAL
3	ARAB	-0.0450	-0.2170	2	0.3209	0.2388	KHAM, SOL, SAF, JAL	QAL, AHM
4	SYR	-0.0383	-0.0817	2	0.3209	0.0891	YAZ, JAN, ASG, LAR	QAL, AHM
5	USISR	-0.0152	-0.0547	2	0.3209	0.1488	KHAM, SOL, SAF, JAL	QAL, AHM
6	NUKE	-1.7888e-05	-1.6172e-04	2	0.3209	0.1086	YAZ, JAN, ASG, LAR	QAL, AHM
7	IRGC	0.0068	0.0224	2	0.3209	0.0215	YAZ, JAN, ASG, LAR	QAL, AHM

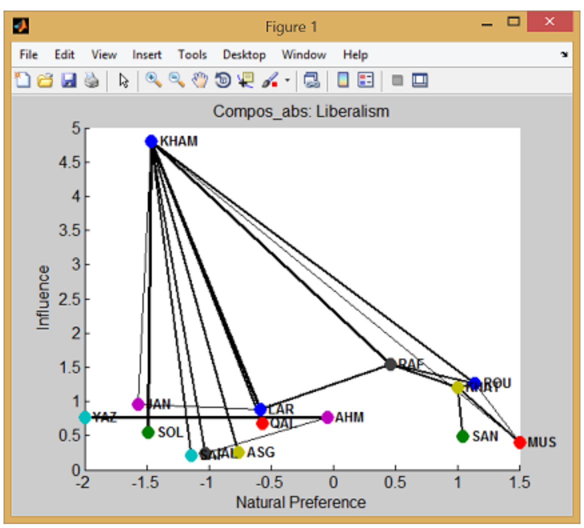
Three network dimensions appear in the table but only 1 and 2 can claim significance. Network Dimension 1 is seen to align significantly with ECON and the plot is shown, revealing a strain between AHM and the other conservatives. The positions of YAZ on the network and issue plots are substantially at odds indicating that this issue could also strain AHM's close relationship with YAZ, requiring either a large change in issue position by one or both or a weakening of their relationship. Network Dimension 2 aligns significantly with the IRGC issue. In the IRGC figure, SAF and SOL are at the right sides of both the network and issue plots whereas LAR and ASG are on the left of both. KHAM is seen to play a bridging role in both the network and issue space.

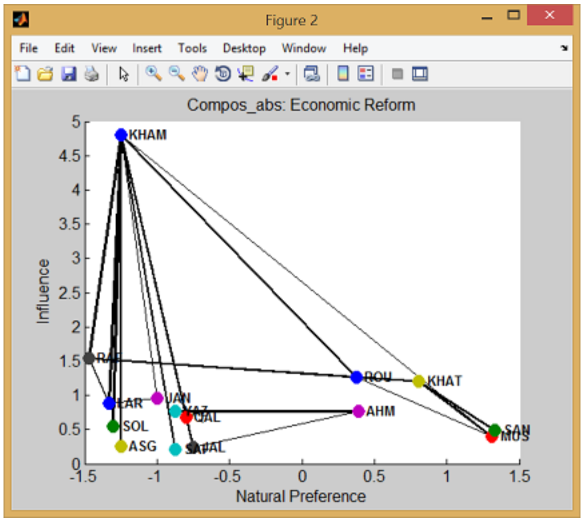




Factional Maps - 1D

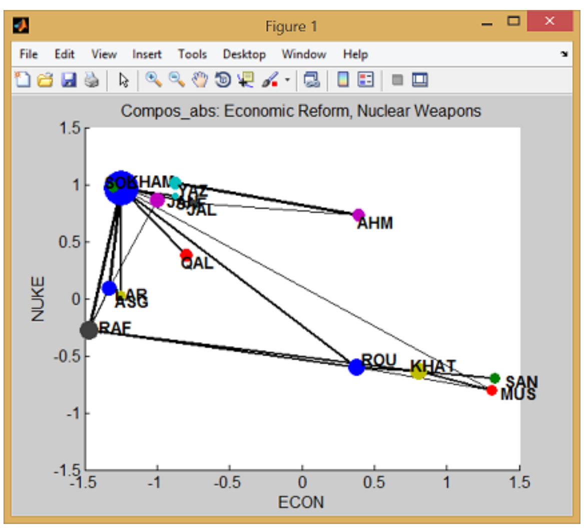
Select *Factional Maps - 1D*. A factional map is generated for each of the figures. It displays three different quantities: (1) the actor issue positions (natural preferences) are on the x-axis; (2) the overall influence (network out-degrees normalized so that the mean is one) is on the y-axis; and (3) the line thickness is proportional to the strength of the symmetrized tie between two actors (weak ties are thresholded). The second two items are the same on all the issue plots. The LIB and ECON issues are shown below. The outsized influence of KHAM and his alignment with the conservaties is clear. In the LIB plot, RAF is seen as a bridge between the reformers and the conservatives by both his intermediate position and his strong links to LAR and KHAM. Because of this position, RAF could also be a swing player.





Factional Map - 2D

Select *Factional Map - 2D*. A menu of issues will appear. As an example, select ECON and NUKE as the issue pair. The issue-space is two-dimensional and actor overall influence is represented by the area of the circles. While there is a central axis between the conservatives in the upper left and the reformers in the lower right, RAF, LAR, and ASG fall into one cluster away from that axis which is very opposed to Economic Reform but is more centrist on Nuclear Weapons policy. AHM also occupies a unique position.



Nonlinear Influence Simulation (1D) Example

Conducting 1D nonlinear influence simulation using Iran example case.

Loading the Case

The case used here is the Iranian leadership case (see the Issue Analysis Example for a brief description).

If not already loaded, load the example case as follows:

1. From the **Cases** menu of the PORTEND™ main window, select *Load Case*.
2. Select *Iran1* from the list of cases and press *OK*.

The **Current Case** box should read *Iran1*.

Initial Steps

1. From the **Outcomes** menu of the PORTEND™ main window, select *Nonlinear Influence (1D)* which opens the Nonlinear Influence Simulation (1D) interface.
2. From the **Input Source** menu, select *SME Arrays*. A file selection box should open in the directory `...\PORTEND\demos\Iran1\input`. You can select multiple SMEs but, for this example, select `Compos_abs_inp`, a composite SME, and click *Open*.

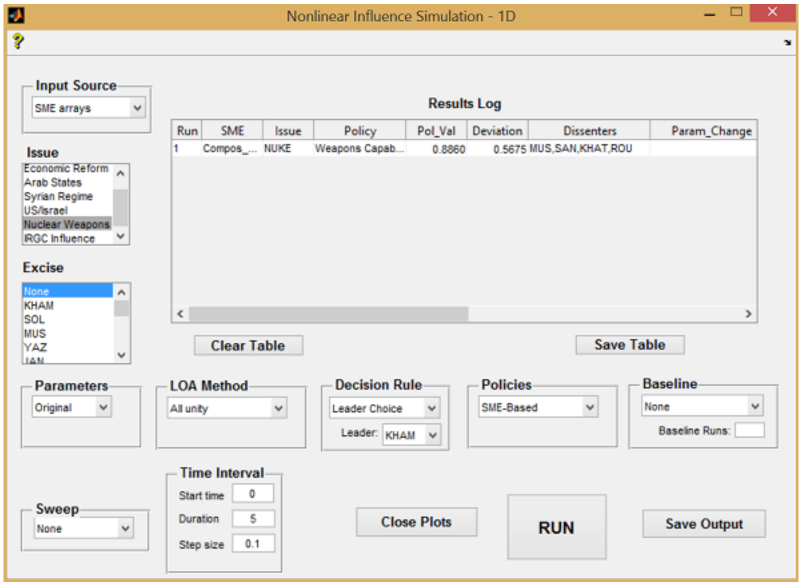
Simulations can now be performed. An example sequence is described below. Note that the sections are intended to be performed in order.

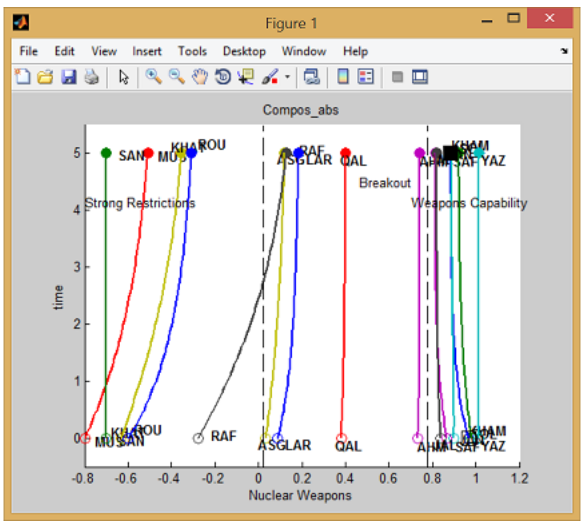
Basic Simulation

An example of a basic simulation is as follows:

1. Under the **Issue** menu, select *Nuclear Weapons*.
2. Under **Policies**, select *SME-Based* which calculates the positions of the different policies based on statements in the SME survey.
3. Press **RUN**.

The **Results Log** table shown below lists the policy name "Weapons Capability" corresponding to the policy value on the issue axis in the *Pol Val* column. The standard deviation of all the final actor positions is shown under *Deviation*. The *Dissenters* column shows that the reformers, with the exception of RAF, dissent, i.e., their final positions are more than one latitude of acceptance (here, equal to one for all) from the final policy value. The plot shows which actors are in each policy region. KHAM does not change his position much, consistent with his outsized influence seen in the Network Analysis Example. RAF is observed to move the most from his natural preference, consistent with the identification as a possible swing player from the network analysis.



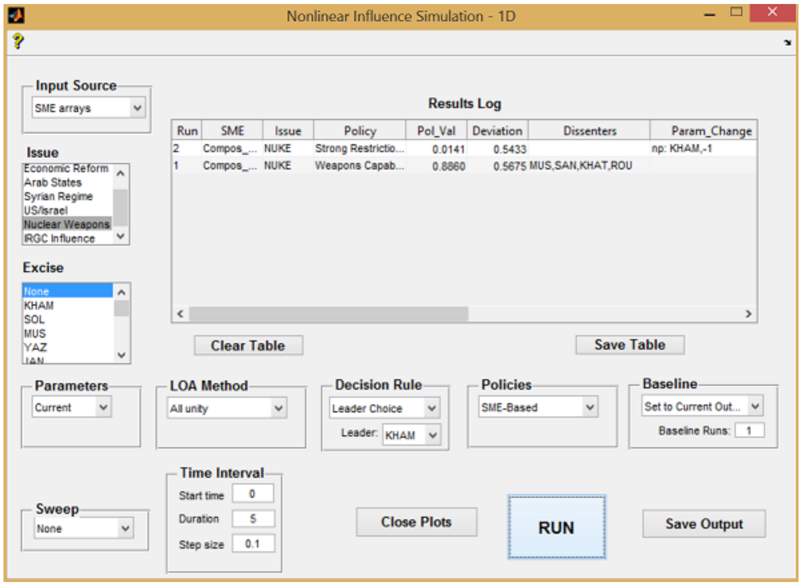


Parameter Change

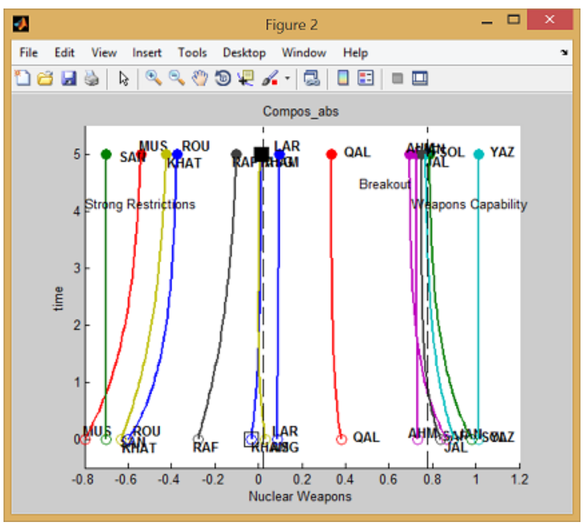
Now investigate the effect of KHAM changing his natural preference to a less pro-NUKE policy:

1. Set the previous run as the baseline by selecting *Set to Current Output* under the **Baseline** menu. The *Baseline Runs* box reads 1.
2. Under the **Parameters** menu, select *Change*. The Change Group Parameters interface appears.
3. Select **Nat. Pref. Shift**. A list of the actors and shift settings appears in the table.
4. Set KHAM to -1.
5. Press **DONE**. The interface closes.
6. Press **RUN**.

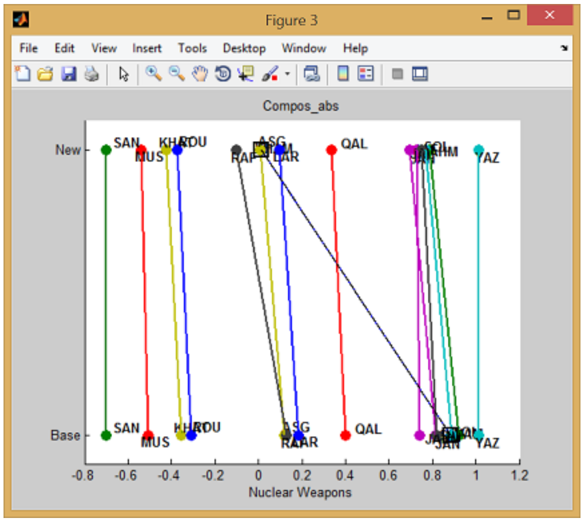
The Results Log below now shows that the policy is Strong Restrictions with a value of 0.0141. Under the *Param Change* column, it indicates that the natural preference (np) of KHAM was shifted by -1.



The plot of actor trajectories below shows the change in KHAM's natural preference toward the center. The other conservatives do not move much toward his position however, likely because it is too far from their positions.



Setting the baseline generates a baseline comparison plot shown below. The bottom shows the final actor positions and policy for the baseline run; the top shows those quantities for the new run. RAF is seen to have the largest change in position due to the parameter change (KHAM's change reflects the parameter shift itself).

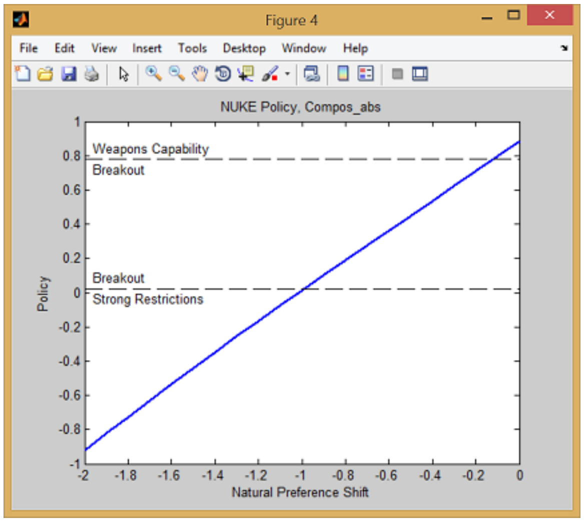


Parameter Sweep

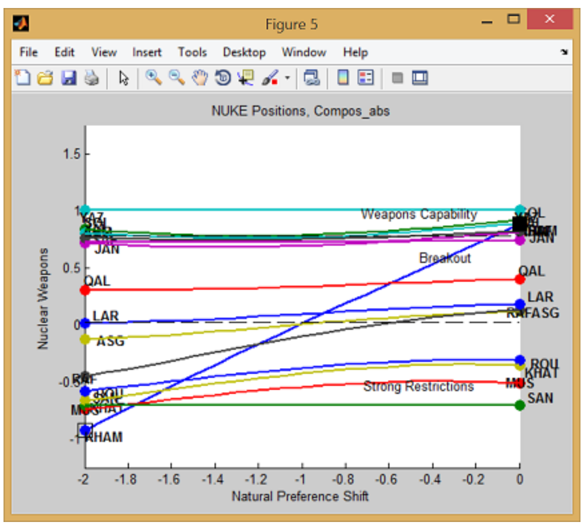
To investigate more fully the effect of KHAM shifting his natural preference, a parameter sweep can be conducted:

1. Select *Nat. Pref. Shift* under the **Sweep** menu. The **Parameter Sweep** interface appears.
2. Select KHAM under the list of actors. Then enter -2 as the start and 0 as the end.
3. Press **DONE**. The interface closes.
4. Press **RUN**. A dialog box appears to say that an actor cannot be included in both a sweep and a point parameter change (since we did not undo the change made to KHAM's natural preference above, which could be done by selecting *Original* in the **Parameters** menu). The box also says that the point change will be ignored so that the shift values refer to shifts from the original SME natural preference value. Select *OK* on the dialog box.

Three plots are generated which are shown below. The first plot shows the policy value as a function of the swept parameter value, in this case KHAM's natural preference shift. We see a simple linear relationship indicative of KHAM's great influence and the Leader Choice decision rule. The policy value crosses from Weapons Capability to Breakout at a shift of -0.15 and then to Strong Restrictions at a shift of about -1.



The second plot shows the individual actor positions (and the policy) as a function of the parameter value. Going from right to left as KHAM's natural preference becomes lower (less pro-NUKE), the conservatives are observed to initally move to lower values but then cease to once KHAM's position becomes too discrepant from their natural preferences. RAF again is observed to be most responsive to KHAM's changing position.



The third plot shows the standard deviation (blue curve) and the parameter intervals over which each actor concurs with the policy (double-ended arrows). The standard deviation shows a minimum near the middle of the Breakout region so this is the policy that KHAM should choose if his goal is to minimize discord within the leadership group. The concurrence intervals show that there is a range between -0.7 and -1 where all actors concur with the policy. Once KHAM moves less than -1, the conservatives start to dissent indicating that he has only a limited room to maneuver should he wish to keep key conservatives, such as the IRGC members SOL and SAF, onboard with his policy.

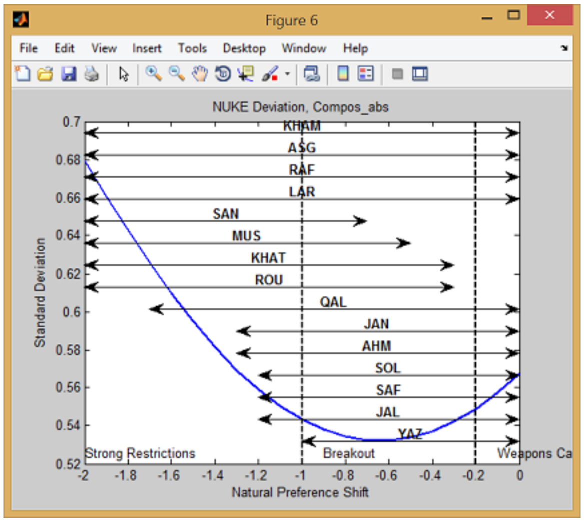


Figure 6
File Edit View Insert Tools Desktop Window Help
NUKE Deviation, Compos_abs
KHAM
ASG
RAF
LAR
SAN
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AHM
SOL
SAF
JAL
YAZ
Strong Restrictions
Breakout
Weapons Ca
Standard Deviation
Natural Preference Shift
0.7
0.68
0.66
0.64
0.62
0.6
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0.56
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-2
-1.8
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-1.4
-1.2
-1
-0.8
-0.6
-0.4
-0.2
0

Appendices

Appendix 1: Parameter Calculation for Group Decision Making Model

Formulas for calculating simulation parameters from SME survey.

Appendix 1
Parameter Calculation for Group Decision Making Model

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September 19, 2014

This report describes the calculation of the following parameters used in the one-dimensional group decision-making model:

1. natural preference (also known as natural bias)
2. coupling strength
3. commitment
4. latitude of acceptance

1 Natural Preference

Input

Attitude statements matrix Y: Actor responses to attitude statements. Statements are along rows and actors along columns; Y_{ij} is the response of actor j to statement i. Values range from -2 (strongly disagree) to 2 (strongly agree). $\mathbf{Y}$ has dimensions $D \times N$ where D is the number of statements and N is the number of actors.

Issue-statement matrix Q: Assignment of attitude statements relevant to issues. Issues are along rows, statements are columns. $Q_{ij} = \{-1, 0, 1\}$. If $Q_{ij} = \pm 1$, then the j^{th} statement is assigned to issue i with a positive (negative) sign indicating that the statement expresses a positive (negative) attitude toward that issue. $Q_{ij} = 0$ indicates that statement j does not pertain to issue i. $\mathbf{Q}$ has dimensions $P \times D$ where P is the number of issues.

Output

Natural preference matrix μ: Actor attitudes for issues. Actors are along rows, issues are along columns; μ_{ij} is the natural preference of actor i for issue j. μ has dimensions $N \times P$.

Calculation

An actor's natural preference for an issue is the average of his responses to the statements corresponding to that issue (including polarity):

$$\mu_{ij} = \frac{1}{n_j} \sum_{k=1}^{D} Q_{jk} Y_{ki}, \tag{1}$$

where n_j is the number of statements assigned to issue j. n_j is found by calculating the number of nonzero entries in the j^{th} row of $\mathbf{Q}$: $n_j = \sum_{m=1}^{D} |Q_{jm}|$. Denoting the $P \times P$ diagonal matrix whose diagonal entries are n_j by $\mathbf{n}$, the matrix equation for the natural preference is

$$\mu = \mathbf{Y}^T \mathbf{Q}^T \mathbf{n}. \tag{2}$$

Implementation

The natural preference is calculated within `groupparams` and uses the function `issueatts`. Further notes are as follows:

1. **Y** is obtained from the "Stances" sheet of survey. Its mean is shifted to zero by `readsurvey`.
2. **Q** is generated by the user via `issuestatements` (as called by `casesetup`).
3. `issueatts` returns the transpose of μ as defined above.

2 Coupling Strength

The matrix of coupling strengths between actors is calculated using these elements: (1) relative influence; (2) persuasibility; and (3) coupling scale. The calculation of these elements is described first followed by the coupling strength.

2.1 Relative Influence

Input

Influence matrix U: Dyadic influence values between actors obtained from survey. U_{ij} is the influence of actor j upon actor i. It can take the range of values $U_{ij} \in [0,4]$. The diagonal elements are set to zero. The dimension of **U** is $N \times N$.

Output

Relative influence matrix r: Normalized influence values between actors. r_{ij} is j's share of the total influence on actor i. **r** has dimensions $N \times N$.

Calculation

The elements of the relative influence matrix are given by

$$r_{ij} = \frac{U_{ij}}{\sum_{m=1}^{N} U_{im}}. \tag{3}$$

It is normalized so that

$$\sum_{j=1}^{N} r_{ij} = 1. \tag{4}$$

Implementation

The relative influence matrix is calculated using `infmat2` (as called by `cplstrength`). Further notes are:

1. **U** is obtained from the "Dyadic Influences Scores" table on the survey. The 1–5 range on the survey is converted to 0–4 using `readsurvey`.

2. **U** as defined above is the transpose of the survey table (after shifting the scale). The transposition is done within `groupparams`.

2.2 Persuasibility

The persuasibility calculation described here uses the influence matrix as input. It is also possible to calculate it from the susceptibility vector.

Input

Influence matrix U: See Sec. 2.1 for description.

Output

Persuasibility vector β: Relative susceptibility to influence. Its elements have values $\beta_i \in [0,1]$ and sum to one. β has dimensions of $N \times 1$.

Calculation

The persuasibility of actor i is given by the i^{th} row sum of **U** normalized by the sum of all the elements of **U** (equivalent to the sum of the row sums).

$$\beta_i = \frac{\sum_{j=1}^{N} U_{ij}}{\sum_{m,n=1}^{N} U_{mn}}. \tag{5}$$

β is normalized so that

$$\sum_{i=1}^{N} \beta_i = 1. \tag{6}$$

Implementation

The persuasibility vector is calculated using `infmat2` (as called by `cplstrength`).

2.3 Coupling Scale

The coupling scale calculation described here uses the susceptibility vector from the survey as input. It is also possible to calculate the coupling scale directly from the influence matrix.

Input

Susceptibility vector η: Susceptibility to influence as directly rated by SMEs. It takes on values in the range $\eta_i \in [0,1]$. η has dimensions of $N \times 1$.

Output

Coupling scale α: Mean share of influence coming from group compared to maximum possible value. It takes on values $\alpha \in [0,1]$. α is a scalar.

Calculation

The coupling scale is the sum of the actual elements of η divided by the maximum possible sum. The maximum possible sum of the susceptibility vector elements is given by $\sum_{i=1}^{N} 1 = N$. This gives

$$\alpha = \frac{1}{N} \sum_{i=1}^{N} \eta_i. \tag{7}$$

Implementation

The coupling scale is calculated using `cplstrength`. Further notes are:

1. η is derived from the "Influence Susceptibility Scores" table of the survey. The survey table values are 1–5 which are shifted to 0–4 (in `readsurvey`) and then divided by the maximum value of 4 (in `groupparams`).

2.4 Coupling Strength

Input

Relative influence matrix r: See Sec. 2.1.

Persuasibility vector β: See Sec. 2.2.

Coupling scale α: See Sec. 2.3.

Output

Coupling strength matrix κ: Dyadic influence values scaled for use in simulation. κ_{ij} is the fraction of the maximum possible influence on i due to actor j. It takes on values $\kappa_{ij} \in [0,1]$ and the diagonal elements are set to zero. κ has dimensions $N \times N$.

Calculation

The coupling strengths are given by

$$\kappa_{ij} = N\alpha\beta_i r_{ij}. \tag{8}$$

In matrix form, this is written

$$\kappa = N\alpha\,\mathrm{diag}(\beta)\,\mathbf{r}, \tag{9}$$

where $\mathrm{diag}(\beta)$ is the matrix with the β_i's along the diagonal and zero elsewhere.

The total coupling strength influencing each actor is equivalent to his network in-degree d_i and is given by:

$$d_i = \sum_{j=1}^{N} \kappa_{ij} = N\alpha\beta_i \sum_{j=1}^{N} r_{ij} = N\alpha\beta_i, \tag{10}$$

where Eq. (4) was used. The mean in-degree is then

$$\bar{d} = \frac{1}{N} \sum_{i=1}^{N} N\alpha\beta_i = \alpha, \tag{11}$$

where the normalization (6) was used. This shows that the coupling scale is equivalent to the mean influence coming into the actors.

Implementation

The coupling strength matrix is calculated in `cplstrength`.

3 Commitment

Input

Coupling strength matrix κ: See Sec. 2.4.

Issue salience matrix W: Issue saliences as derived from survey. Rows are issues, columns are actors. W_{ij} is the salience of issue i to actor j. It takes on values $W_{ij} \in [0,1]$ and is column normalized so that the sum of an actor's saliences across issues is one, $\sum_{i=1}^{P} W_{ij} = 1$. $\mathbf{W}$ has dimensions $P \times N$.

Salience shift factor δ_0: Factor for salience-based shift in commitment. It is a constant which can be set in the range $\delta_0 \in [0,1]$. The current setting is $\delta_0 = 0.5$.

Output

Commitment vector γ: Actor commitments to natural preference for issue being simulated. γ_i is the weight of the self-bias force for actor i. It takes values $\gamma_i \in [0,1]$. γ has dimension $N \times 1$.

Calculation

An unweighted commitment vector $\tilde{\gamma}$ is first calculated neglecting the salience and assuming that for a given actor the sum of his commitment and coupling strengths is one:

$$\tilde{\gamma}_i = 1 - \sum_{j=1}^{N} \kappa_{ij} = 1 - d_i. \tag{12}$$

The salience values for the issue are taken to shift the commitments so that actors with saliences greater (less) than the mean have their commitments increased (decreased) in proportion to the fractional difference from the mean. For an issue m, a salience vector can be defined by $\mathbf{w} = [W_{m1} \ldots W_{mN}]^T$. The mean of $\mathbf{w}$ is written $\bar{w}$. The shift in actor i's unweighted commitment is then given by

$$\Delta\tilde{\gamma}_i = \delta_0 \frac{w_i - \bar{w}}{\bar{w}}. \tag{13}$$

The salience-weighted commitment is then

$$\gamma_i = \tilde{\gamma}_i + \Delta\tilde{\gamma}_i. \tag{14}$$

Any commitments that become negative due to the salience shift are set to zero:

$$\gamma_i = 0 \text{ if } \tilde{\gamma}_i + \Delta\tilde{\gamma}_i < 0. \tag{15}$$

In general, salience weighting makes the sum of the commitment and coupling strengths of an actor no longer equal to one. However, the sum of the unweighted commitment shifts is zero, $\sum_{i=1}^{N} \Delta\tilde{\gamma}_i = 0$ which implies that the salience weighting does not change the mean of the commitment vector. Therefore, the sum of the mean commitment and the mean incoming coupling strength still equals one:

$$\begin{aligned} \bar{\gamma} + \bar{d} &= \bar{\tilde{\gamma}} + \bar{d} && (16) \\ &= 1 - \bar{d} + \bar{d} && (17) \\ &= 1, && (18) \end{aligned}$$

where Eq. (12) was used. Equation (18) is true as long as no commitment had to be set to zero as a result of the salience shifting.

Implementation

The commitment is calculated using `commitment`. Further notes are:

1. **W** is obtained from the "Issue Salience Scores" sheet on the survey. The salience values for a given actor are normalized by dividing by the total allotted point sum. This is done in `groupparams`.

2. Varying the coupling scale for scenario analysis can also cause commitments to become negative in which case they are set to zero.

4 Latitude of Acceptance

There are three different methods for calculating the latitude of acceptance (LOA): (1) Uniform value; (2) Dyadic similarity; (3) SME deviation; and (4) Statement deviation. These methods have different inputs but they all share the same output, the LOA, which will be defined first.

Output

Latitude of acceptance matrix λ: Distance of maximum of coupling function. λ_{ij} is the LOA for actor i with respect to messages from actor j. Its value must be positive $\lambda_{ij} > 0$ (diagonal elements are set to one). Additional constraints on the value are made by the various methods. λ has dimensions $N \times N$. If the method yields an issue-dependent LOA, the issue m is denoted by a superscript λ_{ij}^{m}.

4.1 Uniform Value

Calculation

In this method, the LOA is set to a constant for all elements, $\lambda_{ij} = \lambda_0 \ \forall i, j$. Typically, the choice is $\lambda_0 = 1$. This implies that successive values (1–5) on the attitude scale for the survey are separated by one LOA and that the entire scale spans four LOA.

Implementation

The uniform value method is implemented in `groupparams`.

4.2 Dyadic Similarity

The dyadic similarity method calculates a separate LOA for each (directed) dyad. It assumes that an actor i will have a larger LOA for an actor with similar positions on the issues salient to i compared with an actor with positions dissimilar to i. Because it uses all the issues in calculating the LOA, the LOA matrix is issue-independent.

Input

Natural preference matrix μ: See Sec. 1.

Issue salience matrix W: See Sec. 3.

Maximum LOA value $\lambda_{\max}$: Upper limit of LOA scale range. The default value is $\lambda_{\max} = 1.5$.

Minimum LOA value $\lambda_{\min}$: Lower limit of LOA scale range. The default value is $\lambda_{\min} = 0.5$.

Calculation

For each actor i, the salience-weighted natural preference matrix is denoted ω^i. The element ω^i_{mn} is the natural preference of actor m for issue n multiplied by the salience of n to actor i:

$$\omega^i_{mn} = W_{ni}\mu_{mn}. \tag{19}$$

The matrix of similarities χ is found by calculating the correlation of the salience-weighted natural preferences. Denoting the vector of i's salience-weighted natural preferences for actor j by ω^i_j the similarity of j for actor i is:

$$\chi_{ij} = \mathrm{corr}(\omega^i_i, \omega^i_j). \tag{20}$$

The minimum and maximum values of χ are then found, denoted by $\chi_{\min}$ and $\chi_{\max}$ respectively. A rescaling factor b_0 and a translational shift a_0 are then defined:

$$\begin{aligned} b_0 &= \frac{\lambda_{\max} - \lambda_{\min}}{\chi_{\max} - \chi_{\min}}, && (21) \\ a_0 &= \lambda_{\min} - b_0\chi_{\min}. && (22) \end{aligned}$$

Each element of the LOA matrix is then rescaled and shifted so that they range between $\lambda_{\min}$ and $\lambda_{\max}$:

$$\lambda_{ij} = b_0 \chi_{ij} + a_0. \tag{23}$$

Note that there is no issue index in λ_{ij} as the LOA matrix is the same for all issues. If one were to try to further scale the LOAs by the range of natural preferences for a given issue, then one would be discarding the fact that the attitude scale has an absolute meaning in terms of the level of disagreement. Doing so would imply that all issues have the same basic level of contention regardless of whether the natural preference range is small or large.

Implementation

The dyadic similarity method is implemented in `dyadicsimloa`. Further notes are:

1. This method requires more than one issue.
2. The salience values for a given actor are normalized in `dyadicsimloa` (not in `groupparams` as for the commitment calculation).

4.3 SME Deviation

The SME deviation method assumes that an actor's LOA for a given issue is reflected by uncertainties in his natural preference as gauged by its standard deviation across SMEs. An actor has the same LOA with all other actors for a given issue.

Input

SME-specific natural preference matrix μ^k: This is the same as the natural preference matrix defined in Sec. 1 but indexed by the k^{th} SME. There are K total SMEs.

Minimum LOA value $\lambda_{\min}$: Minimum allowable LOA used to reset zero or very small LOA values. The default value is $\lambda_{\min} = 0.1$.

Calculation

Let $\bar{\mu}_{im}$ denote the mean over all K SMEs of the vector of actor i's natural preference values for issue m, $[\mu^1_{im} \dots \mu^K_{im}]$. The LOA for actor i for issue m is then calculated as the standard deviation:

$$\lambda^m_{ij} = \left[\frac{1}{N-1} \sum_{k=1}^{K} (\mu^k_{im} - \bar{\mu}_{im})^2 \right]^{\frac{1}{2}} \quad \forall j. \tag{24}$$

If any LOAs are found to be lower than the threshold $\lambda_{\min}$, they are reset to $\lambda_{\min}$.

Implementation

The SME deviation method is implemented using `devloa`. Further notes are:

1. This method requires more than one SME.

4.4 Statement Deviation

The statement deviation method calculates an actor's LOA for a given issue as the standard deviation of his responses to the statements corresponding to that issue. It yields issue-dependent LOAs but not dyad-dependent ones.

Input

Natural preference matrix μ: See Sec. 1.

Attitude statements matrix Y: See Sec. 1.

Issue-statement matrix Q: See Sec. 1.

Minimum LOA value $\lambda_{\min}$: Minimum allowable LOA used to reset zero or very small LOA values. The default value is $\lambda_{\min} = 0.1$.

Calculation

Recalling from Sec. 1, that the number of statements assigned to issue m is n_m and the total number of statements is D, the LOA is calculated by

$$\lambda_{ij}^{m} = \left[\frac{1}{n_m - 1} \sum_{k=1}^{D} (Q_{mk} Y_{ki} - \mu_{im})^2 \right]^{\frac{1}{2}} \quad \forall j. \tag{25}$$

If any LOAs are found to be lower than the threshold $\lambda_{\min}$, they are reset to $\lambda_{\min}$.

Implementation

The statement deviation method is implemented in `stmdevloa`. Further notes are:

1. The method requires more than one statement per issue.

2. The survey statements have not yet been designed with this method in mind. There should probably be at least five statements per issue.

3. The composite SME was found to yield considerably lower LOAs than the mean of the LOAs from the individual SMEs. This is likely the result of the averaging process by which the composite SME is formed reducing the variation in statement responses.

Appendix 2

Data Processing for Applications of Dynamics-Based Models to Forecasting

Chapter 16

Data Processing for Applications of Dynamics-Based Models to Forecasting

Michael Gabbay, University of Washington

1. Introduction

The “Forecast” operational capability tracks and projects change along multiple dimensions in sociocultural entities and phenomena of interest. This chapter addresses issues related to representing a particular sociocultural system in a way that involves (1) only data available for an actual, ongoing situation that can be used to (2) reveal meaningful changes in the system over time and (3) implement models that can help users to anticipate those changes. These three elements distinguish data processing issues for forecasting from those in the “Understand” capability area, in which historical – not only current – data can aid in understanding sociocultural systems. They also separate forecasting from the “Detect” area, in which it suffices for algorithms to find patterns in data without predicting future behavior or supporting causal models of how the system evolves. This chapter centers on selected aspects of data processing relevant to dynamics-based models, i.e., models that posit causal mechanisms of system evolution, rather than purely statistical models, and illustrates the discussion with applications in the domain of political and insurgent network dynamics.

The first section of this chapter briefly describes dynamics-based modeling methodologies and presents a model of group decision making as an example that will help guide the subsequent discussion. Dynamics-based models involve an important distinction between variables and parameters and the second section of the chapter discusses the requirements and considerations involved in calculating their values. Calculating parameters is particularly difficult and the extent to which they can be determined influences whether the output of a model can be evaluated with respect to an actual time scale or only with respect to equilibrium outcomes.

The chapter then presents two examples of applications, both concerning leadership elites and their organizations. Research has largely overlooked the behavior of leaders and organizations amidst the surge of interest in social media, population sentiment, and “big data,” yet this type of data is particularly important in tracking and anticipating change on time scales of operational concern with regard to entities subject to operationally relevant levers of influence. These two examples, presented in the fourth and fifth sections, use different types of input data. The first involves the use of expert judgments in conjunction with the group decision-making model. The second involves the representation and modeling of insurgent network behavior and shows how the ideologies, policies, and relationships among insurgent groups can be constructed using rhetoric as data and tracked over time. For the insurgent network application, the chapter presents a stochastic model of insurgent cooperation at the tactical level and compares the model results with the network's evolution as observed in the data. Finally, the chapter provides a brief discussion of gaps in knowledge and future research directions related to data processing and forecasting, focusing on areas relevant to dynamics-based models and political application domains.

2. Dynamics-Based Models

In dynamics-based models, variables can evolve based on their present state and their interactions with other variables. Thus, a variable can be affected by self-feedback, as in an exponential growth or decay situation in which the rate of change of the variable is proportional to its value, and by feedback from other variables in the system, as in a predator-prey model where the rate at which the number of prey animals declines depends on the number of predators. Typically, these models posit causal mechanisms that underlie the forms of the feedbacks included. For example, in a model that treats the spread of a revolutionary ideology like the spread of an epidemic, the rate at which the number of people "infected" with the ideology increases is taken to be the product of the present number of already infected people and the number of people who are susceptible but not yet infected (Epstein, 1997). This assumes that each interaction between an infected and susceptible person has a certain chance of resulting in a new adherent to the ideology, as in person-to-person disease transmission.

This product interaction between variables is an example of a nonlinear interaction. Nonlinear models can accommodate complex behaviors such as abrupt, discontinuous changes in the nature of the system's behavior. Such sharp transitions are often of highest importance in sociocultural forecasting, e.g., will a localized uprising result in a mass revolution? Indeed, the epidemic model contains a critical threshold, called the reproduction rate, above which the epidemic or revolution will take off but below which it will fizzle out. Purely statistically based approaches such as regressions are ill suited to forecasting sudden transitions in sociocultural contexts, which is one reason why this chapter focuses on dynamics-based models. In addition, statistically based models often provide little insight into how interventions into a situation will play out; therefore, they cannot be applied to analyzing courses of action for the purposes of the "Mitigate" capability area. However, regardless of whether one uses dynamics-based models or statistical methods, sociocultural forecasting remains a difficult task, largely due to the lack of appropriate empirical data.

There are various ways of implementing dynamics-based models, three of which are briefly mentioned here: differential equations, stochastic models, and agent-based models (for a more detailed description of various modeling methods, see the Computational Models chapter in the Forecast section). Differential equations give mathematical expressions for the rates of change in a system of variables that can then be solved, computationally or analytically, to show the values of the variables over time. The equations evolve variables in continuous time (difference equations are the discrete-time analog). The epidemic model noted above is most readily expressed and analyzed in differential equation form. The

Lanchester model for combat dynamics is another differential equation that may be familiar to some readers due to its prevalence in the combat simulations used in operations research (Epstein, 1997). Differential equations are typically deterministic in that the future evolution of the variables is precisely determined by their initial values (although they can be adapted to accommodate stochastic forcings). A class of critical transitions in which the state of the system can change suddenly and discontinuously, known as "bifurcations," can occur in nonlinear differential equations; for example, old states become unstable and disallowed while new stable states emerge.

Unlike differential equations, stochastic models allow variables to evolve in a random rather than a deterministic manner. Also, these models typically represent temporal evolution discretely rather than continuously. Often the models assume a Markov process in which the probabilities of the various future states of the system depend only on its current state. In a stochastic simulation of the epidemic model of ideology diffusion, one could simulate all the individuals in a population, endow them with different characteristics, and allow infected individuals to meet and infect susceptible individuals with given probabilities. Stochastic models are often used in simulating processes that occur over networks, such as opinion change and cultural transmission, and in simulating network evolution itself, as in the model of insurgent cooperation presented below. Scale-free networks – characterized by power law distributions in which a relatively few nodes have a greatly disproportionate degree (number of ties) – can be generated by a stochastic "preferential attachment" model in which new nodes have a higher probability of linking to high-degree nodes than to low-degree ones (Newman, 2010). Stochastic models can exhibit critical transitions resulting in abrupt changes of state in the form of phase transitions at large population sizes.

At its most general, agent-based modeling involves the specification of interaction rules for a system of agents in a group or population. These rules can be deterministic or probabilistic and expressed in terms of mathematical formulas, similar to differential equations and stochastic models. However, agent-based modeling diverges most notably from these other modeling approaches when the rules are essentially algorithmic: specifically, agent behavior is governed by a relatively complex process that accounts for strategies, heuristic rules, experience from prior interactions, and learning. Consequently, agent-based models can simulate very rich behavior, although the downside for forecasting purposes is that they usually require more data to implement empirically and more computational resources to simulate the parameter space for assessing potential outcomes. Examples of applications of agent-based models to social systems in specific real-world cases include the modeling of social identity dynamics (Alcorn et al., 2011) and political party competition (Laver and Sergenti, 2012).

Group Decision Making Model

To provide a specific example of a dynamics-based model and a more concrete basis for the discussion of empirical implementation issues, we now consider a nonlinear model of group decision making – one that has been applied for forecasting purposes (Gabbay, 2007, Gabbay, 2013). The model captures the evolution of group member policy positions under the influence of group discussion and their own ideological preferences. Although the model is formulated as a differential equation system, it is expressed here only in terms of qualitative rules to avoid becoming bogged down in mathematical detail. The rules are:

1. Each group member's current position is affected by two forces: the *self-bias force* and the *group influence force*.
2. The self-bias force is the tension that an individual feels when his current position is different from his *natural bias* position, which is determined by ideological and strategic preferences such as the relative importance placed upon military, diplomatic, economic, and political factors. The self-bias force:
   a) Acts in the direction of the natural bias.
   b) Has magnitude proportional to the difference between the individual's current position and natural bias.
   c) Increases in proportion to the individual's *commitment* to his natural bias.
3. The group influence force is the tension that an individual group member feels when his position is different from those of other group members.
   a) The total group influence force on an individual is the sum of the coupling forces resulting from his pairings with all the other group members.
   b) For a given pairing, the coupling force on an individual acts in the direction of the position of the other member of the pair.
   c) The magnitude of the coupling force increases approximately linearly for small position differences but weakens for differences greater than the individual's latitude of acceptance.
   d) The coupling force that member j exerts on member i is scaled by the *coupling strength*, which characterizes factors such as how often j communicates with i about the policy matter at hand, their relative status, i's perception of j's credibility or expertise, and the importance that i attaches to group influence.

At high disagreement levels (i.e., large differences in natural bias) the model displays nonlinear behaviors, including sharp transitions between qualitatively distinct outcomes as the coupling strength increases; asymmetric, majority rule outcomes resulting from symmetric conditions; the existence of multiple stable outcomes for the same parameters; and the greater facility of less dense networks to reach decisions and reduce discord. These behaviors are not present at low disagreement levels.

3. Variables and Parameters

All dynamics-based models are characterized by variables and parameters. Variables define the state of the system as it evolves in the model over time. In the model above, the policy positions of the individual group members are the state variables. Other examples of variables in sociocultural models include cultural norms, attitudes, popular support levels for government or insurgents, sizes of social movements, violence levels, and network ties among individuals or organizations. For forecasting applications, the state variables should be either: (1) indirectly related to the ultimate object of interest, in the sense that the application is intended to predict and measure an aggregated function of the state variables; or (2) the objects of ultimate interest themselves, in that the application is intended to predict and measure the future values of the state variables. For the group decision-making model, the first case would apply if the researcher's ultimate goal were only to forecast the final policy decision of the group. This can be done by aggregating the final policy positions of the individual group members according to a suitable decision rule (e.g., leader choice, weighted averaging, consensus). The second case would apply if the researcher also wanted to predict which group members will support the policy and which ones will dissent, which can be determined from the distance between their final position and the final policy. Another example of aggregating variables, as in (1) above, is a model of insurgency in which the state variables are the attitudes of individual population members toward the government and toward the insurgents, but the application seeks to forecast only the overall levels of support.

Parameters are model quantities that characterize the system exogenously, i.e., they are not affected by the state variables. Parameters play a key role in dynamics-based models in determining how variables interact with each other and the environment. In the epidemic model of militant ideology spread, parameters determine the ease with which the ideology can spread between individuals and the rate at which infected individuals are removed by government repression or counterinfluence. Referring to the group decision-making model above, the natural bias, is used to set the initial positions of the members; the commitment scales the strength of the self-bias force for a given displacement of each member's policy position from her natural bias; a person's latitude of acceptance sets the range of policies surrounding her own position that she will entertain and serves as the source of the nonlinear interactions; and the coupling strength between individuals scales the impact of relational factors on how effective a person will be at swaying another person's position. For stochastic models, the parameters determine how the transition probabilities between states depend upon the state variables.

Modelers usually take parameters as constant, but can make them time-dependent as well. Given the complexity of sociocultural systems, variables often provide feedback to parameters, but as long as the time scale of that feedback is slow relative to the time scale at which variables evolve one can still consider the parameters as effectively exogenous. If that feedback occurs at a rate comparable to the change in the variables, however, then the modeler faces a coevolution problem and should redefine the "parameters" as state variables. The group decision-making model example assumes that the members' changing policy positions have no impact on the coupling network between group members. This is reasonable for a relatively short decision-making episode, but if the model were examining a long time scale—say years—then policy positions would probably affect relationships under the operation of the homophily principle: "birds of a feather flock together."

One of the primary difficulties – perhaps the greatest one – in forecasting sociocultural phenomena is that many of the concepts used in social science theory as well as in common discourse are not readily quantifiable. Power, ideologies, policies, attitudes, beliefs, grievances, trust, relationships, disagreements, utility, etc., do not come in standard units like watts, meters, or amperes. For instance, a social network matrix may use a single number to represent ties between individuals, but that does not capture the complexity of social relationships.

"Forecast," therefore, occupies a thorny middle ground in the abstract-to-concrete data spectrum between the "Understand" and "Detect" capabilities. To help *understand* general decision-making phenomena, one can model policy spaces in the abstract, but one must assign actual policies to policy space coordinates in order to *forecast* whether a particular country's leaders may decide upon war in a given situation. For *detection*, on the other hand, very specific, concrete, and readily quantified data such as the frequency of conversations may suffice to identify central individuals or communities in, say, an email network. However, that is not equivalent to identifying the top leaders who make strategic decisions in times of crisis and the relationships of authority and influence between them. Consequently, a key challenge in forecasting is to construct meaningful variables and parameters from relatively specific, more quantifiable, lower level data that can be reasonably mapped onto more abstract, higher order theoretical concepts.

This construction of conceptually broader variables and parameters is necessary not simply to connect with social science theory but also to reduce the dimensionality of the space of variables that must be predicted. Considering the group decision-making context, a group member's natural bias policy may be a function of her beliefs about the facts, the relative importance that she accords to the different components of the problem – military, diplomatic, economic, domestic political – and how she evaluates the policy options for each of those components. Although an analyst may be able to assess those factors for each group member, no model can be expected to predict the changes in each of those factors due to group interactions. It is therefore necessary to reduce the dimensionality of the space of the state variables by, for instance, combining the above factors to represent policy positions in a one or two-dimensional space. The subsections on analyst input and insurgent rhetoric present examples of ways to construct ideology and policies from lower level data.

Variables and some kinds of parameters can be calculated by applying the defining formula or algorithm to data representing a single time instant or interval independently of other times or other variables. However, feedback parameters in particular, which necessarily involve rates of change over time or the strength of interaction among variables, cannot truly be calculated solely on the basis of a predefined formula or algorithm that operates on data representing only one time. Ideally, one would measure the behavior of the state variables over time and then fit the parameters to the data, similar to the way parameters are measured experimentally in physical systems. This is also analogous to statistically based pattern recognition and forecasting methods in which an in-sample is used to fit parameters that are then applied to out-sample data. Such a fitting procedure can be used to determine parameters in sociocultural systems, but typically is difficult to carry out to much precision due to the lack of sufficient data points over time and the relatively large amount of noise in the data, among other factors. This is particularly true of the conflict-ridden and chaotic regions of interest to the U.S. military. When fitting parameters to existing data is not an option, then modelers can choose parameter values in an a priori manner based on considerations of what constitutes reasonable values or ranges. Simulations can then sweep over a patch of parameter space in order to determine the sensitivity of the outcomes to changes in the parameters. Laver and Sergenti (2012) offer a thorough and candid discussion of the issues involved in parameter calculation for an agent-based model of political party competition.

4. Forecasting Modes

Dynamics-based models can be applied for forecasting purposes in a variety of modes. The modes available for a given application depend on the nature of the data. One mode involves predicting, in a probabilistic way, the evolution of variables that can change in a more-or-less continuous fashion over time: for instance, the levels of popular support for an opposition movement among different segments of the population. This would correspond to true forecasting in that one assigns time-dependent probabilities of the various possible states of the system, as is done in weather forecasting. However, as discussed above, this remains an ambitious goal for most models of sociocultural dynamics due to the limitations in measuring variables and parameters (as well as model uncertainty itself, a topic not considered in this chapter). Although it would be technically possible to develop simulation software that makes explicitly probabilistic forecasts, doing so could well be counterproductive in the absence of accurate and precise estimates of model variables and parameters. Otherwise, end users, accustomed to reliable weather forecasts, could be lulled into a false sense of confidence by the simulation's provision of numerical probabilities and, consequently, might be greatly disappointed by the inevitable large mismatch between the forecasts and reality.

A looser mode of forecasting can be applied to key events, such as conflicts, decisions, and alliance composition, which can be treated as one-off occurrences. In these instances, one relaxes the requirement that the model make forecasts over time and simply assumes that the time window is sufficiently long to allow the system to reach equilibrium, issues of timing. In the group decision-making model, the time scales that enter into the commitment and coupling scale parameters are not usually known, which precludes such a model from being used to forecast the evolution of the group members' policy positions in real units of time. However, the equilibrium positions themselves do not depend on the time scales, and so the model can still be used to predict the final decision and its supporters and dissenters, on the assumption that the debate persists until equilibrium. This equilibrium approach significantly eases data demands; many dynamics-based models use this mode in practice.

Sensitivity analyses in which simulations cover a region in the parameter space can also be employed for forecasting purposes. If the outcome does not vary significantly as parameters sweep over a range of reasonable or likely values, then the model user can conclude that the outcome is highly probable. Alternatively, the simulations may reveal a range of possible outcomes. These may include potential outcomes (e.g., alliance configurations) not anticipated prior to the simulation. Sensitivity analysis may also reveal that the outcome can change dramatically with only a small shift in parameter values, as would be consistent with a bifurcation or phase transition.

As an illustration, consider a group decision-making model in which all group members are connected with the same coupling strengths and have initial opinions (natural biases) symmetrically distributed around zero. More specifically, consider a three-person group in which a centrist is bracketed by two equidistant extremists. Standard intuition would anticipate either a deadlock or various shades of compromise around the centrist position, consistent with final states that are symmetric about the middle, as shown in Figure 1(a) and

(b) for deadlock and compromise respectively. However, at sufficiently high levels of initial disagreement, another outcome can result in which the centrist swings toward one of the extremes (depending on random perturbations), corresponding to a majority rule situation favoring one side of the policy axis. In this case the system reaches an asymmetric final state as observed in Figure 1(c) (Gabbay and Das, 2012). Even a small change in coupling strength can produce a transition to the majority rule outcome zone from either the deadlock or compromise zones. If the simulation of a leadership group showed such behavior, analysts could be prepared for an extreme decision rather than deadlock or compromise.

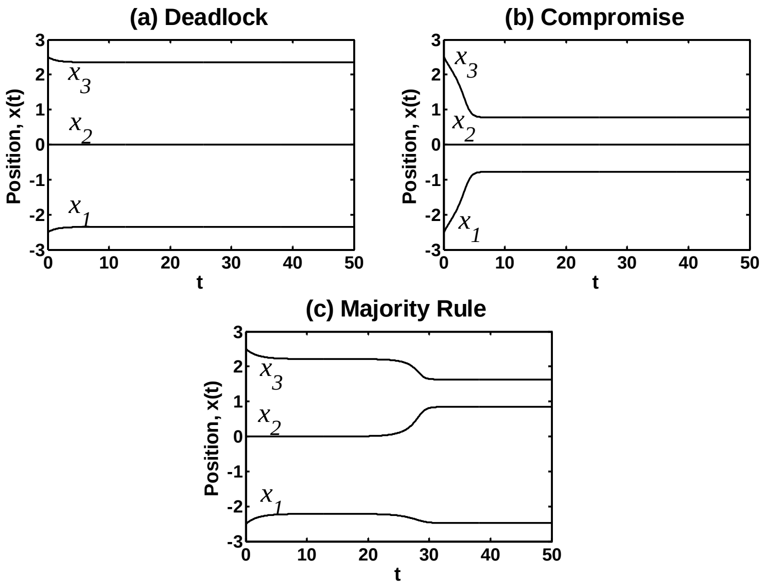

Figure 1. Group decision-making simulation of member positions over time in triad network (chain topology) with symmetric coupling strengths and natural bias distributions: (a) symmetric deadlock outcome at low coupling strengths; (b) symmetric compromise outcome at high coupling strengths; and (c) asymmetric majority rule outcome at intermediate coupling strengths.

Finally, dynamics-based models can be used to conduct scenario analyses to forecast the effects of specific hypothesized contingencies or conditions. These analyses can be implemented by particular variable or parameter settings that represent exogenous impacts on the system due to events or actions outside the dynamics of the model. For example, in a group decision-making situation, one can simulate the effect upon the policy outcome of a rupture in the relationship between two group members due to a personal dispute unrelated to the policy context. This could be done by nulling or severely attenuating their mutual coupling strengths, possibly in combination with other parameter changes.

5. Analyst Input for Group Decision Making

The two principal sources of data for calculating the "soft" variables and parameters (opinions, beliefs, ideologies, norms, social identities, etc.) needed as model input are analyst (subject matter expert) judgments and content analysis. Currently, analyst-based input represents the prevalent form of input (e.g.,Alcorn, et al., 2011, Feder, 2002, Gabbay, 2013), but the use of content analysis-based input is growing, especially given recent advances in automated text analysis. This section briefly discusses the use of analyst input in conjunction with the group decision-making model described above. The next section describes an application of content analysis using rhetoric as input data for the context of insurgent network dynamics.

Figure 2 shows the processing chain to implement the model for specific leadership groups using analyst judgment for input. The modeler obtains this input from a survey given to one or, preferably, many analysts. A composite analyst can be formed by averaging the survey responses of the individual analysts. The aggregation of individual surveys allows analyst judgments to be synthesized independently of each other. This minimizes the chance that social pressure will alter individual judgment, as can happen if the modeler elicits inputs in an oral discussion with a group of analysts – a common practice in other models of group decision-making used within the national security community (Bueno de Mesquita, 2009). Note that results can be generated on the basis of individual surveys as well. This permits comparison of the results obtained from individual analysts with the composite analyst and with each other, thereby providing a way of stimulating debate about differences between analyst viewpoints.

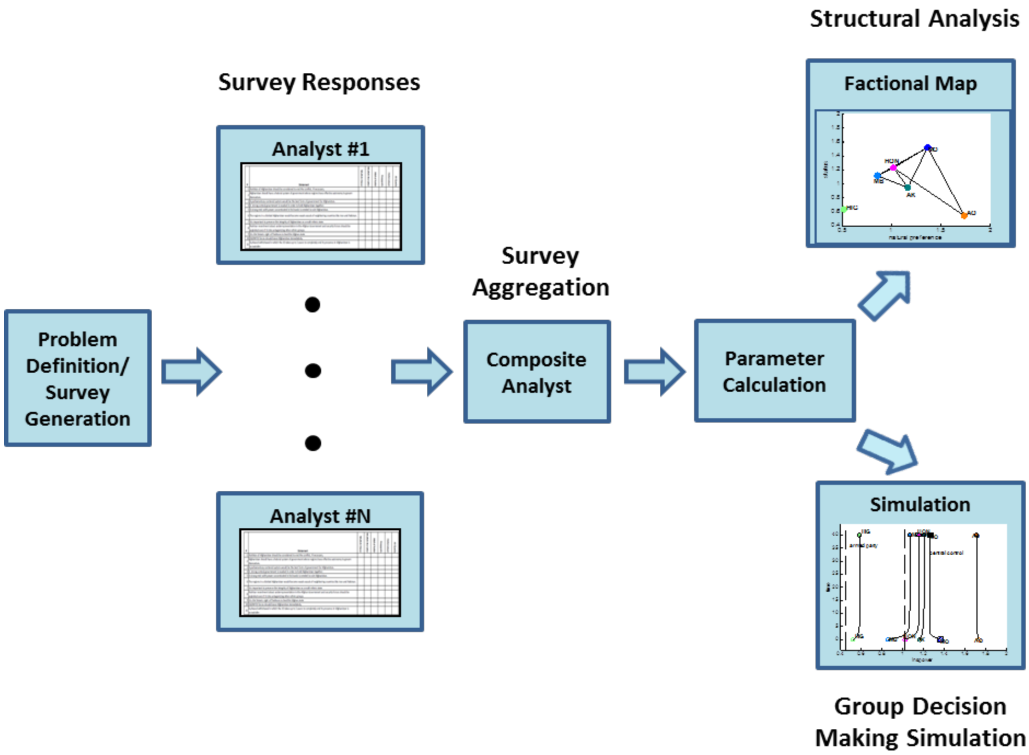

Figure 2. Overview of analyst input-based implementation of group decision-making model.

Another innovation in this implementation methodology is the use of an attitude scaling technique to assess member ideological and policy positions. The natural bias, which is typically taken as the initial position of a group member, is constructed on the basis of a series of attitude statements for which the analyst rates the level of agreement or disagreement as if she were the group member in question, as shown in Table 1. This enables assessment of several different facets of the policy problem that can then be aggregated to calculate the natural bias. Also, modelers can probe the deeper structure of the policy space by using matrix decomposition methods such as principal component analysis. This approach elicits analysts' expertise on group member policy preferences without demanding that they directly perform the abstraction needed to create a policy axis or space itself — a task that the modeler accomplishes instead.

Table 1. Sample attitude statements assessing ideological and policy preferences from an analyst survey on Afghan government elites. Analysts are asked to rate member attitudes on a five-point scale ranging from "strongly disagree" to "strongly agree."

	Statement	**Karzai**	**Fahim**	**Khalili**	**Rabbani**	**Dostum**	**Nur**
1	Partition of Afghanistan should be considered to end the conflict, if necessary.						
2	Afghanistan should have a federal system of government where regions have effective autonomy to govern themselves.						
3	Karzai's efforts to concentrate power in the presidency show that the Afghan Constitution should be changed to institute a parliamentary -centered system of government.						
4	A strong central government is needed in order to hold Afghanistan together.						
5	A strong leader with power concentrated in his hands is needed to rule Afghanistan.						
6	The regions in a divided Afghanistan would become weak vassals of neighboring countries like Iran and Pakistan.						
7	It is important to preserve the integrity of Afghanistan as a multi-ethnic state.						
8	It is the historic right of Pashtuns to lead the Afghan state.						

6. Rhetoric Input for Insurgent Network Dynamics

This section presents an application using input derived from content analysis – both automated and manual – in which the data source is Iraqi insurgent rhetoric. It describes methods for quantifying insurgent ideology, targeting policy, and cooperative relationships. Those three elements roughly correspond to insurgent ends, means, and allies respectively: critical components of their strategic behavior and decision making. These elements can be used to track insurgent behavior over time and as inputs in models for forecasting insurgent dynamics. A model of insurgent tactical cooperation is presented at the end of this section as an example of how such data can be used for simulating insurgent network evolution.

The modelers collected data for the 18 Iraqi Sunni insurgent groups listed in Table 2, spanning the time from mid-2003 through mid-2009. This time span is divided into three periods: (1) Period 1, August 2003–July 2005; (2) Period 2, August 2005–July 2007; and (3) Period 3, August 2007 – July 2009. The data set consists of roughly 2,000 translated insurgent statements from jihadist websites and interviews of insurgent group officials in print and broadcast media as provided by the U.S. government's Open Source Center.

Table 2. Sunni insurgent groups in Iraq used in content analysis of insurgent rhetoric.

Group	**Symbol**	**Overall Classification**	**Islamist Ideology**	**Time Periods**
Al-Qaida in Iraq	AQI	Jihadist Salafist	Salafist	1,2,3
Ansar al-Sunnah Army (Ansar al-Islam: post Dec. 2007)	ASA	Jihadist Salafist	Salafist	1,2,3
Islamic Army in Iraq	IAI	Nationalist	Salafist	1,2,3
Mujahidin Army	MA	Nationalist	Salafist	1,2,3
1920 Revolution Brigades	1920RB	Nationalist	Unspecified	1,2,3
Islamic Front for Iraqi Resistance	JAMI	Nationalist	Muslim Brotherhood	1,2,3
Rashidin Army	RA	Nationalist	Unspecified	1,2,3
HAMAS-Iraq	HAMI	Nationalist	Muslim Brotherhood	3
Fatihin Army	FA	Nationalist	Salafist	2,3
Iraqi Jihadist Leagues	IJL	Jihadist Salafist	Salafist	2,3
Shield of Islam Brigade	SIB	Jihadist Salafist	Salafist	2,3
Ansar al-Sunnah Shariah Commission	ASA-SH	Nationalist	Salafist	3
Just Punishment Brigades	JPB	Jihadist Salafist	Salafist	2,3 (part)
Abu Bakr al-Siddiq Salafi Army	ABSSA	Jihadist Salafist	Salafist	2,3
Islamic Jihad Brigades	ISJIBR	Jihadist Salafist	Salafist	1,2
Victorious Sect Army	VSA	Jihadist Salafist	Salafist	1,2
Saad Bin Abi Waqqas Brigades	SBAW	Jihadist Salafist	Salafist	2,3
Army of Naqshabandi Order	NAQSH	Nationalist (Baathist)	Sufi	2,3

Ideology

Ideology is quantified by the concept of a *conflict frame*. The conflict frame of a political actor, such as an insurgent group or government leaders, is defined on the basis of the set of out-group parties perceived as current or potential enemies and in-group parties perceived as allies or as a base of support (Gabbay and Thirkill-Mackelprang, 2011). This definition stems from social identity theory and its implications for political rhetoric. *Conflict parties* consist of broad groups such as the incumbent government, ethnic or religious groups and their leadership classes, and foreign states. The mathematical formalism for conflict frames relies on the frequency with which specified marker terms appear in actor rhetoric and their in/out-group valences. Figure 3 is a conceptual diagram of the elements involved in the conflict frame calculation procedure. Sample marker terms and associated in- and out-groups are given in Table 3.

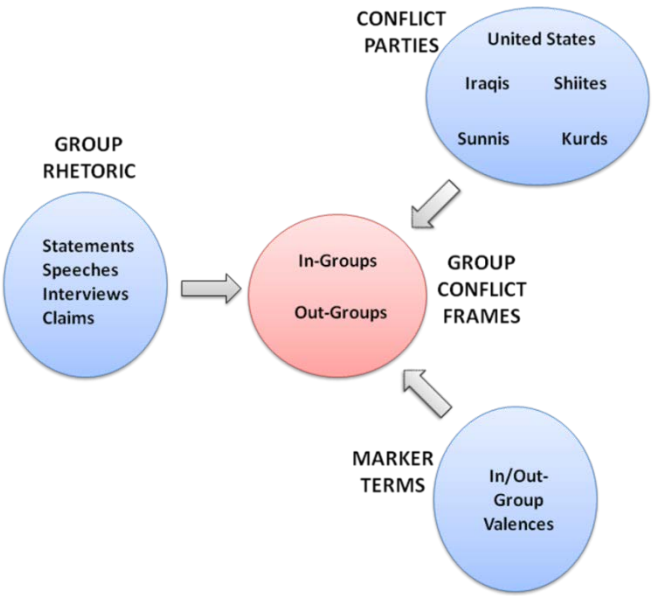

Figure 3. Conceptual diagram of conflict frame method of quantifying ideology.

Table 3. Examples of marker terms and associated in-groups and out-groups for Iraqi insurgents.

Marker Term	In-Groups	Out-Groups
agent government		Iraqi Government
apostate government	Sunni Civil Society	Iraqi Government
companions of the prophet	Sunni Civil Society	
cross worshippers	Sunni Civil Society	United States
Iraqis	Iraqi Civil Society	
Iranian occupation	Sunni Civil Society	Iraqi Government, Shiite Political Parties
occupier		United States
rejectionist	Sunni Civil Society	Shiite Civil Society
rescue council		Sunni militias (awakening councils)

Each marker term is assigned a valence for all the conflict parties to which it refers: positive (+1) for in-groups, negative (–1) for out-groups, and zero for neutral references. A conflict party's *salience* to the actor is essentially the frequency with which marker terms referring to that party appear in the actor's rhetoric, regardless of valence. The actor's *attitude* toward the party is related to the relative frequency of positive and negative references to it. The attitude weighted by the salience represents the actor's *orientation* toward the party. An actor can have a highly negative attitude toward a conflict party but a low orientation value if the actor seldom refers to the party, which hence has low salience. The collection of orientation values for all the conflict parties forms the conflict frame of the insurgent group.

This procedure is automated following the construction of the initial dictionary and valence matrix and therefore can be updated in near-real time to track ideological shifts and divisions within the actor ensemble. An actor's conflict frame vector, composed of the actor's orientations toward the conflict parties, is the primary output of the algorithm. Another way of analyzing the data, however, is by considering certain master frames, which can be given intuitive interpretations. A master frame consists of a specified subset of out-groups and in-groups. The extent to which an actor espouses a given master frame can be quantitatively gauged by how closely its conflict frame aligns with the master frame – mathematically via the inner product of the corresponding vectors. Two master frames dominate for the Iraqi insurgents: (1) the resistance frame that pits Iraqis as in-group against the United States as out-group and (2) the sectarian frame that pits Sunnis as in-group against Shiites as out-group.

Figure 4 shows the conflict frames for the Iraqi insurgent groups over the three time periods.[1] The Jihadist groups—particularly the two major ones, Al Qaida in Iraq (AQI) and Ansar al-Sunnah—tend to fall on the high end of the sectarian frame and the low end of the resistance frame. The Nationalists, especially "pure" Nationalist groups such as the 1920 Revolution Brigades, JAMI, and the Rashidin Army, have lower sectarian frame values and high resistance values. However, it is important to note that the figures show a spectrum rather than two widely disjoint clusters of Jihadists and Nationalists, as would be implied by such a binary analytical classification. This spectrum quality and the locations of individual groups in the master frame coordinate space have meaningful implications for cooperative behavior among insurgent groups. The first two Nationalist alliances to nucleate comprised neighbors in the Period 2 master frame space: (1) the Jihad and Reform Front consisting of IAI, MA, FA, and ASA-SH; and (2) the Jihad and Change Front consisting of 1920RB and RA. This suggests that the conflict frame construct can provide meaningful and predictive input to models of insurgent alliance formation.

[1] The groups ABSSA and ISJIBR are not included (documents were not preprocessed to remove extraneous text).

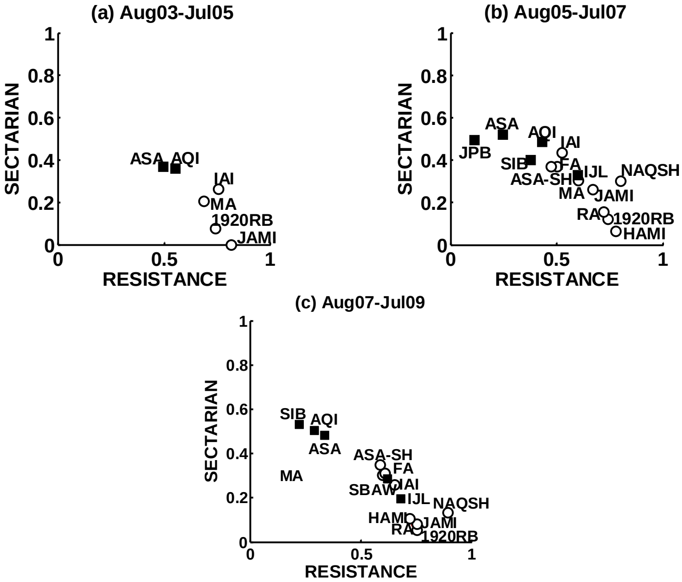

Figure 4. Master frames for Iraqi insurgent groups: (a) Aug03–Jul05; (b) Aug05–Jul07; (c) Aug07–Jul09. Jihadists in black squares, Nationalists in white circles**.**

Tracking changes is one of the objectives of the Forecast area and the time-dependent behavior of the conflict frames can be tracked for either individual groups (as in Figure 4) or the whole ensemble. For example, in tracking changes in the balance between the two master frames for whole ensemble of groups, Figure 5(a) shows that the sectarian frame component increases relative to the resistance frame from the first to the second period, even among the Nationalists, and then wanes again in the third. This tracks the transition into a Sunni-Shiite civil war during 2006 and 2007 and the subsequent decline in sectarian violence. Ideological dissension within the insurgency can be tracked by looking at the frame deviation: i.e., how spread out the groups are in the space of master frames. Figure 5(b) shows the frame deviation in the resistance-sectarian master frame space. The deviation starts out low during the first period but increases and plateaus for the second and third periods. This corresponds to the character of factional relations within the insurgency. Early on, the groups were relatively united, but the transition to a sectarian civil war was a key factor in producing a rift between the Jihadist and Nationalist wings of the insurgency, eventually leading to the formation of the anti-AQI Awakening Councils and open fighting between Nationalist groups and AQI.

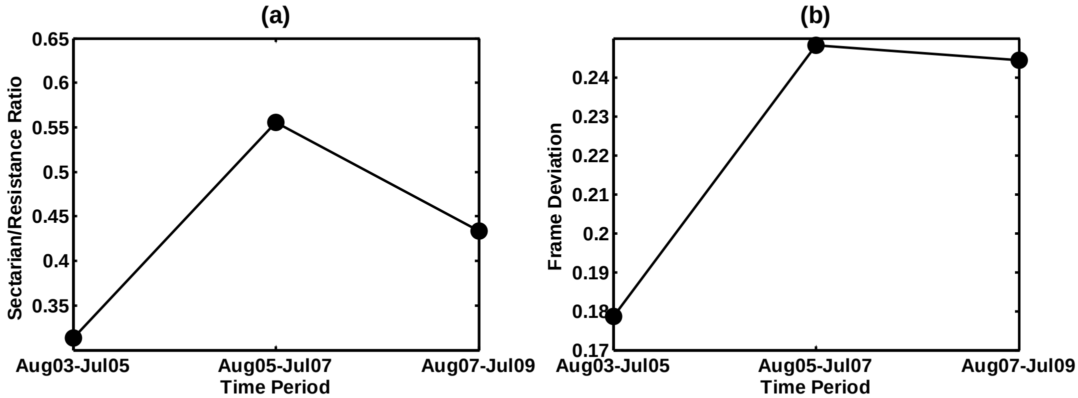

Figure 5. Temporal tracking measures for Iraqi insurgent ideology: (a) Ratio of mean sectarian frame value to mean resistance frame value; (b) Standard deviation in group two-dimensional frame positions from mean position of sectarian and resistance frames.

Targeting Policy

To construct the targeting policy variable, the portfolio of target classes—US troops, Iraqi security forces, Shiite militias, government officials, civilians, etc.—claimed by different insurgent groups is considered (Gabbay and Thirkill-Mackelprang, 2011). The targeting policy scores each insurgent group by the average legitimacy of its target class portfolio, where the "legitimacy" of each target class is the acceptability of attacking it as determined by the prevalence, within the set of insurgent groups, of claims and statements supporting targeting the class vs. condemnations of doing so. A high targeting policy corresponds to a more discriminate or selective use of violence, while a low one indicates more expansive and controversial targeting practices. Implicit in this construction is that distance along the targeting policy axis is related to the extent of disagreement. This reflects that disagreement over the legitimacy of different types of targets has often been the primary source of dissension within Islamist insurgencies (Hafez, 2003).

Figure 6 shows insurgent group targeting policies over the second and third time periods. The groups are arranged along the vertical axis in ascending targeting policy order so that groups at the bottom have lower targeting policies. The figure shows that the Jihadists tend to have lower targeting policies and Nationalists higher ones. However, similar to conflict frames, this reflects a spectrum rather than a binary distribution. Like conflict frames, targeting policy can also be used to track dissension among insurgent factions; the standard deviation of the targeting policy increases over time in tandem with the actual rise in dissension within the insurgency (Gabbay and Thirkill-Mackelprang, 2011).

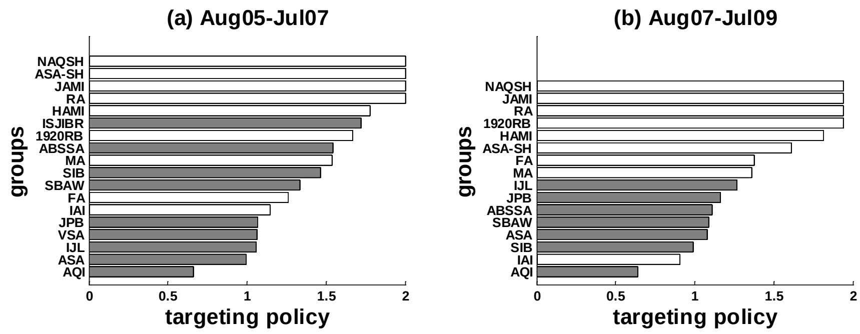

Figure 6. Targeting policies for Iraqi insurgent groups: (a) Aug'05–Jul'07; (b) Aug'07–Jul'09. Jihadists in gray, Nationalists in white.

Cooperative Networks

The rhetoric-based methodology constructs networks representing cooperative relationships among insurgents at both the leadership and rank-and-file levels. Leadership relationships among groups are gauged by the number of joint communiqués they issue. A joint communiqué is a statement signed by two or more groups, indicating the presence of communication and some level of agreement among the leadership of the groups issuing it. Furthermore, it demonstrates a willingness of the groups involved to be publicly associated with each other. At the rank-and-file level, the model uses the number of joint operations between groups. Typically, only one of the participants makes a claim of joint operations. Such operations indicate tactical coordination among insurgent groups, although presumably a group's leadership would have to approve the public disclosure of such cooperation. Figure 7(a) shows the joint operations network for the third time period; Figure 7(b) shows the simulated version, which is discussed presently.

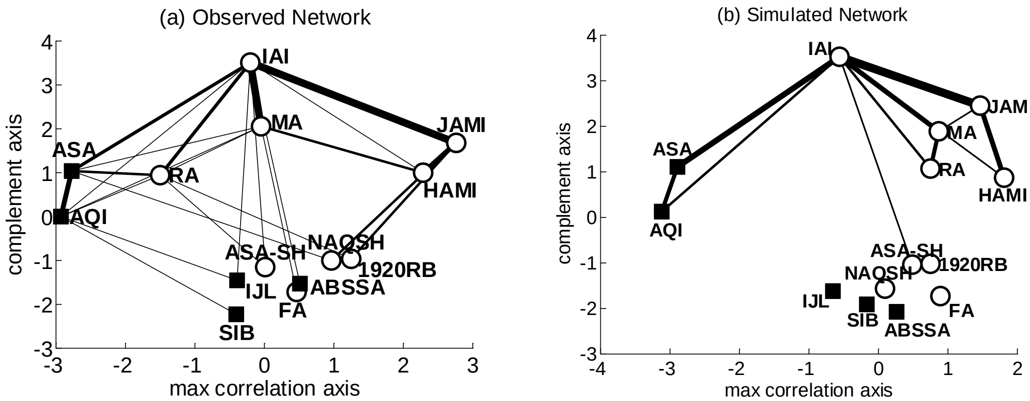

Figure 7. Joint operations networks for Aug '07–Jul '09: (a) observed; (b) simulated. Jihadists in black squares, Nationalists in white circles.

Application to Modeling Insurgent Tactical Cooperation

The elements of the above representation can serve as input data for a stochastic model of insurgent tactical cooperation (Gabbay and Thirkill-Mackelprang, 2010). The model variables are the numbers of joint operations between insurgent group pairs, whereas targeting policy and the leadership network ties are taken as fixed parameters. The model assumes that each insurgent group has a number of foot soldier field units that may cooperate with the units of other groups. The model describes the probability that some unit from group *i* will conduct a joint operation with some unit from group *j*. It assumes that the joint operation process depends on the group sizes, the number of prior joint operations between units of *i* and *j*, their tendency to interact with similar other groups, their targeting policies, and the presence or absence of leadership relationships. Figure 8 shows a diagram of the process.

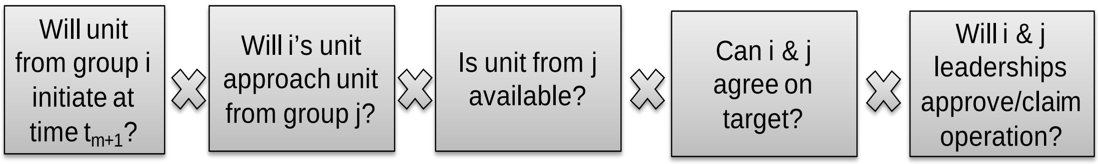

Figure 8. Simulated process for evolution of a joint operations network.

An important feature of this model is its positing of roles for both horizontal interaction in which foot soldier units can, on their own initiative, cooperate with units from other groups and a hierarchical process through which group leaderships can decide whether or not to let such operations go forward and/or claim responsibility for them if they occurred. This horizontal and hierarchical blending manifests the hybrid nature of insurgent groups that mix formal and informal organizational structures.

Figure 7 above displays a comparison of the observed and simulated networks for the third time period. The simulated network represents the average over 500 simulation runs. The simulation used the state of the joint operations network in the previous period to represent the initial conditions, but used the targeting policies and leadership network of the third period to better assess the tactical cooperation model itself. Model parameter values (other than the fixed targeting policies and leadership networks) were chosen based on intuitively reasonable estimates and set to be the same for the simulations of the second and third period networks; some variation of parameters was conducted but an extensive search of the parameter space to optimize results was not performed. The visualizations show good agreement in the placement of the insurgent groups; only MA and RA are significantly out of place in the simulation (readers should ignore the links in the simulation plot as they have been thresholded to unclutter the graphic). For forecasting purposes, analysts could employ such a model to predict changes in patterns of insurgent cooperation under different scenarios, such as increased dissension over targeting practices.

7. Future Research Directions

This section identifies some current shortcomings in existing capabilities for data processing in the Forecast capability area and suggests future research directions. By necessity, the discussion is selective and emphasizes areas related to the types of application domains presented in this chapter. It also stresses the need to develop data appropriate for dynamics-based models, advocates more dedicated efforts to collect and process data on elites and their organizations, and suggests the development of multi-level network representations as one avenue for structuring this data.

Data processing is a critical enabling capability in the application of dynamics-based models for forecasting purposes. Better data will naturally lead to better models. While this is true of both statistical and dynamics-based models, the latter ultimately hold more promise. Statistical methods are powerful because they often can be applied to data in a context-independent way, but they have serious limitations when applied to the contexts of particular concern to national security analysts, planners, and policy makers—situations often marked by crisis, conflict, and chaos. For example, regression models can endeavor to forecast future violence levels in a conflict using only a time series of past violence levels without any need to know about the power balance, constraints, and internal dynamics of the warring parties. However, this results in futures that hardly differ from the recent past. Regression models, for instance, would never have anticipated the precipitous drop in violence in Iraq due to the synergistic effects of the Sunni Awakening and the US troop “surge” in 2007, when the Sunnis, squeezed on both sides by the extremist AQI and the newly empowered Shiite majority, decided to side with the United States against AQI (Biddle et al., 2012). Given that most forecasting of social and political systems occurs within a statistical modeling framework, more focused research is needed on aligning data processing with dynamics-based models.

It is not only the availability of more data that is important but also the intelligent processing of that data into quantities that are (1) theory-driven and (2) operationally relevant. The first criterion refers to the need for compact, low-dimensional quantitative representations that correspond to theoretical constructs from social science. The second refers to the need to include variables and parameters that can change on time scales of operational concern or can be influenced on those time scales using operationally available means. Imposing these criteria will facilitate model development and the practical application of computational models to forecasting. In such applications the models will address the issues most relevant to intelligence analysts and operational planners (thus tying into the “Mitigate” capability area) and can be used to forecast changes over a relatively small number of dimensions. Operational relevance has not been a strength of most extant instability forecasting work that relies on structural factors such as low economic development, regime type, ethnic fragmentation, mountainous terrain, existence of a territorial dispute, etc. These factors may predispose a country to conflict but indicate little about the situation-specific triggers, timing, and levers of influence that may exacerbate or ameliorate a conflict situation (O'Brien, 2010).

The insurgent network application presented above illustrates a theory-driven quantitative representation of soft, intangible variables for organizations. The definition of insurgent targeting policy – a one-dimensional measure – is motivated by social science research showing the importance of disagreement over targeting practices, such as indiscriminate attacks against civilians, in the relations between insurgent groups. The application of social identity theory to political rhetoric prompted the use of the conflict frame as an ideology variable. The theory's definition in terms of in-groups and out-groups makes the data well suited to serve as input to models of alliance dynamics, as its correspondence to the formation of alliances among Iraqi insurgent groups makes clear. It can also be an input to models of insurgent strategic violence and is in fact correlated with targeting policy (Gabbay and Thirkill-Mackelprang, 2011). The number of parties to the conflict gives the dimension of the conflict frame vector, which can be further reduced by projection onto a master frame space, as described earlier in this chapter. Both targeting policy and conflict frames have operational relevance because they influence and reflect significant changes in the nature of the conflict itself and, hence, evolve on operational time scales. In addition, they can inform analysis and planning of operational means such as information operations or selection of particular groups for targeting or negotiations.

Additional types of data and improved processing techniques focused on elites and their organizations – whether in the government or its opposition, at a national or a local level – would be particularly helpful in developing theory-driven and operationally relevant forecasting methods. The decisions and actions of these individuals and groups directly and immediately shape the trajectories of crises and conflicts. The recent surge of research on popular opinion, driven by the availability of social media and automated tools for sentiment analysis, has overshadowed the significance of elites and their organizations. Although generic sentiment analysis software could be applied to the rhetoric of political leaders and organizations, it would likely not provide a useful data processing tool for forecasting their behavior. Standard sentiment analysis methods, originally developed for contexts such as movie and consumer product reviews, have not proven to work well on the discourse of political elites, whose rhetoric must often be circumspect and cast in neutral language, relying more on nouns and topic emphasis than on adjectives, which carry positive or negative sentiment in ordinary speech (Yu et al., 2008). However, researchers have used other types of text mining algorithms, such as support vector machines, to successfully classify elite political rhetoric (Diermeier et al., 2012).

In support of this call for more research on elite and organizational data, it has been found that the presence of factionalism within a state plays a very significant role in forecasting political instability via statistical methods (Goldstone et al., 2010). This implies that accurate and timely metrics of elite or organizational factional dissension, like the conflict frame-based measure of ideological dissension in Figure 5(b), should improve forecasting of crises such as coups, rebellions, and civil wars. Researchers may find it particularly worthwhile to integrate data on elites with political event data that encode interactions such as violence between political actors. Automated methods for extracting event data from news feeds have been developed for various regions and contexts (Schrodt, 2012). In particular, some researchers have suggested the integration of event data with leadership rhetoric as a way to improve forecasts of the onset of intrastate conflicts such as insurgencies (Tikuisis et al., 2013).

It is important to stress, however, that forecasting elite and organizational behavior should constitute a goal in its own right and not just an auxiliary input for conflict prediction. This will stimulate the development of such data at a greater temporal resolution, sufficient to track the evolution of these groups and more fully encompass the range of factors that drive their behavior. Elites respond to the preferences of their own organizational constituents, the actions of other organizations and their leaders, and the sentiment of the broader population. Standard social network analysis would focus on constructing ties only within the set of elites or between organizations, but researchers should develop data that enables representation of new multi-level networks, including the ties connecting leaders and the activist or rank-and-file components of their organizations as well as the ties among activists of different organizations.

The use of both leadership tie indicators (joint communiqués) and tactical unit tie indicators (joint operations) represents a step toward better representations of multi-level networks that can more fully account for elite policy and alliance dynamics. For example, it is possible that the standard mechanism of social influence, in which actors with strong ties grow more similar to each other (Friedkin & Johnsen, 2011), appears to be violated at one level but can be explained by ties between levels. Such a dynamic explains the shift of the IAI to a more extreme targeting policy in the Aug07–Jul09 time period (Figure 6), even though its leadership ties in both periods were exclusively with Nationalist groups with more moderate targeting policies, which could have been expected to lead to a moderation of the IAI's targeting policy. This apparent violation of the social influence mechanism can be explained by the fact that the IAI was responding to dissent from its hardline rank-and-file constituents over its recent alliance with JAMI and HAMI (Gabbay & Thirkill-Mackelprang, 2010). The inclusion of the rank-and-file level can therefore account for forces on elites that could produce seemingly anomalous effects when viewed within a single-level network model.

Representations of multi-level networks should also include policies and ideologies. This calls for data that can be used to construct policy and ideological orientations of organizational membership elements. Social media could provide one source of data on rank-and-file opinions, as could analyst judgments. Another approach would involve looking at the rhetoric in media affiliated with elites whose audiences consist of their organizational members or support bases. For example, an analysis of the rhetoric of Afghan government elites found that the statements of the individual leaders themselves were often substantially different, and usually milder, than the rhetoric of their affiliated media, perhaps indicating the more hardline beliefs of their bases of support (Gabbay, 2011). This also highlights the value of incorporating into models data that connect elites with media outlets and media outlets with their audiences.

In conclusion, this chapter has highlighted aspects of the empirical implementation of computational models for forecasting purposes. The discussion has focused on dynamics-based models, which have the greatest potential to address the most operationally challenging and valuable types of forecasting questions but also make the greatest demands upon data processing. Quantitative variables and parameters for low-dimensional models must be coaxed from high-dimensional and often fundamentally qualitative data – a problem compounded by the often contested, chaotic, and covert nature of the environments and adversaries of most concern to national security intelligence analysts, planners, and policy makers. The analyst survey and rhetoric analysis methods described in this chapter represent two different approaches for tackling this problem. In practice, researchers who develop dynamics-based models for forecasting purposes often place a particular model formulation first and then seek to collect and process data appropriate for their model. Although this section has made a few relatively specific suggestions for future research, a broader recommendation would be to pursue a more integrated approach to developing dynamics-based models for forecasting. Such an approach should center on the construction of general quantitative variables appropriate for a particular domain, such as political unrest, insurgencies, or proliferation, which are sufficiently rich to enable the application of dynamics-based models (as opposed to purely statistical models), thereby encouraging a range of approaches that can be more readily evaluated.

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Appendix 3

Leadership Network Structure and Influence Dynamics

Leadership Network Structure and Influence Dynamics

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Introduction

Pivotal policy decisions in states or organizations like militant movements are often made by a small group of top leaders (Hermann, 2001). This speaks to the importance of developing systematic methods for improving the ability to understand and anticipate the dynamics of leadership groups. This chapter describes a quantitative methodology for the analysis and modeling of leadership networks which leverages research in complex systems, in particular nonlinear dynamical systems theory (Strogatz, 1994) and network science (Newman, 2010). The nonlinear systems element is the model of social influence dynamics which can exhibit complex phenomena such as large, discontinuous transitions (bifurcations) as a parameter is varied and non-trivial interactions with network structure. Factional and other divisions within leadership networks can induce meaningful structure in them; algorithms developed in complex networks research for analyzing community structure can probe this factional structure and, crucially, relate that structure to policy divisions. Investigation of both the network and issue space, as well as their integration, is a core focus of the methodology and is accomplished statically via structural analysis and dynamically via the nonlinear social influence model which evolves leader positions on issues in response to their mutual influence over their network of ties.

This chapter introduces a recently developed prototype software package, PORTEND, that provides a user interface for the analysis and simulation methods. PORTEND's analytical capabilities are illustrated for an application to Iranian leadership elites regarding seven major issues with a particular focus on whether their nuclear technology capabilities should or should not be constrained and subject to international monitoring. Previous applications of the methodology to Russian and Afghan leadership networks have been reported elsewhere (Gabbay, 2007a, Gabbay, 2013). The factional structure of the Iranian leadership group is analyzed first based on their positions on the issues, then with respect to the network of inter-actor influence relationships, and finally by a synthesis of the issue and network data. Moving from structural analysis to simulation, a qualitative description of the nonlinear social influence model is presented followed by application of the simulation to the nuclear issue and discussion of its implications with respect to Iranian decision making concerning the nuclear negotiations that took place from 2013-15.

PORTEND Software

PORTEND (Political Outcomes Research Tool for Elite Network Dynamics) integrates quantitative techniques from nonlinear systems theory and network science to aid the analysis of policy and factional outcomes with respect to the internal dynamics of a system of political actors. The political actors may be individual leaders or organizations within a government or movement. The outcomes of concern may be policy decisions, winning and losing factions, the positions of individuals, or the potential for issues to cause dissension or factional realignment. Political actors are represented mathematically with respect to their preferences on one or more issues, the saliences of those issues, the network of inter-actor influence, and actor power and susceptibility to influence. The data from which these quantities are calculated is obtained from surveys given to expert analysts. PORTEND imports these surveys and aggregates them to form a composite analyst if desired. It then allows for structural analysis regarding issues and the inter-actor network and for the simulation of social influence and group decision making outcomes. The analyses can be performed for the composite analyst or separately for the individual analysts. An overview of the methodology is shown in Figure 1. PORTEND is currently in a prototype stage of development and is implemented in Matlab.

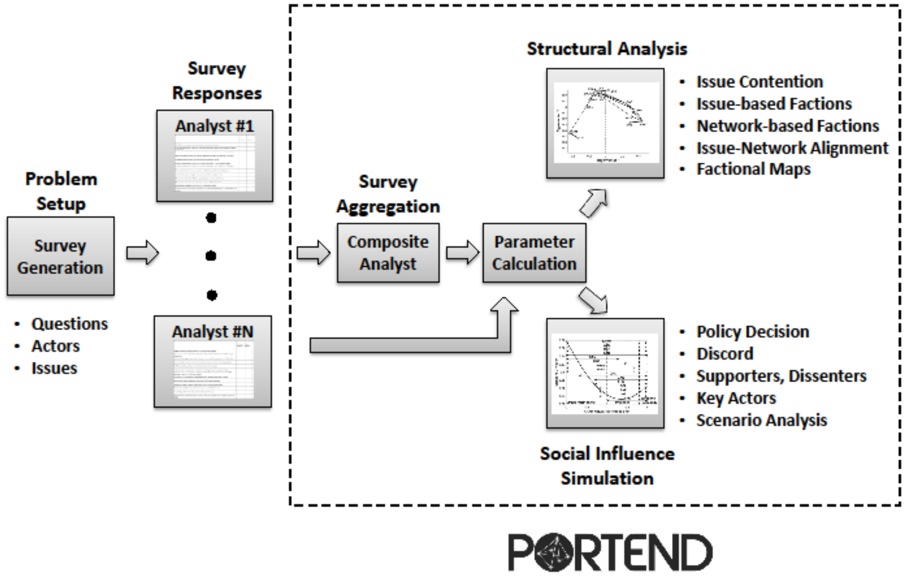


Figure 1. Methodology overview.

Iran Application

This section introduces the Iranian leadership case study which will be used to illustrate the capabilities of the methodology implemented within PORTEND in this chapter. The case study, which was initiated in 2013, considered fifteen top members of the Iranian leadership, as identified by analysts of Iranian politics (Table 1). A survey was developed and then completed by two Iran experts in the autumn of 2013. The elements of the survey will be discussed in the next section. While a major concern of the study involved the Iranian nuclear program, the broader context of Iranian elite politics was also of interest and so the survey included the seven issues below (abbreviations in parentheses):

- Liberalism (LIB): The proper role for Western culture, Islam, media sources, and democratic institutions.
- Economic Reform (ECON): Whether economic policies should benefit the current elites or a wider set of interests.
- Arab States (ARAB): Whether Iran's peers in the Arab world are potential allies or enemies.
- Syrian Regime (SYR): Whether the Assad regime in Syria should be supported.
- US/Israel (USISR): The extent to which Iran should confront the U.S. and Israel.

- Nuclear Issues (NUKE): The extent to which Iran should develop nuclear technology.
- IRGC Influence (IRGC): The appropriate role for the Islamic Revolutionary Guard Corps (IRGC).

Actor (Abbr.)	Role/Notes
Ali Hoseini Khamenei (KHAM)	The supreme leader, the highest political and religious authority in the Islamic Republic of Iran.
Qasem Soleimani (SOL)	Commander of the Quds Force, a unit of the Islamic Revolutionary Guard Corps (IRGC).
Mir Hossein Musavi (MUS)	Prime Minister of Iran from 1981 to 1989. In 2009 he was the reform candidate for president, around whom the Green Movement coalesced. He has been under house arrest since February 2011.
Mohammad Taqi Mesbah Yazdi (YAZ)	A hardline cleric and politician. He is a member of Iran's Assembly of Experts and is seen as the most conservative cleric in Iran.
Ahmad Janati (JAN)	A hardline cleric and chairman of the Guardian Council.
Asadollah Asgaroladi (ASG)	An important businessman with interests in exports, banking, real estate and healthcare. President of several of Iran's international Chambers of Commerce.
Ali Akbar Hashemi-Rafsanjani (RAF)	Served as president of Iran from 1989 to 1997 and chairman of the Expediency Council.
Ali Ardeshir Larijani (LAR)	Current chairman of the Iranian Parliament and former secretary of Iran’s Supreme National Security Council.
Yousef Sanei (SAN)	An Iranian scholar and Islamic theologian and philosopher. He serves as a Grand Marja of Shia Islam.
Mohammad Baqr Qalibaf (QAL)	The current mayor of Tehran.
Yahya Rahim Safavi (SAF)	An Iranian military commander and former Chief Commander of the IRGC.
Mahmud Ahmadinejad (AHM)	The former president of Iran.
Seyyed Mohammad Khatami (KHAT)	President of Iran from 1997 to 2005. One of Iran’s most prominent reformers.
Saeed Jalili (JAL)	Secretary of Iran’s Supreme National Security Council, the equivalent of the U.S. National Security Council.
Hassan Rouhani (ROU)	The current president of Iran.

Table 1. Iranian elites in case study. The abbreviations used in plots are shown in parentheses. Information on roles is as of late 2013.

The analytical questions of interest included:

- Will Iran agree to a nuclear deal that places strong restrictions on enrichment?
- Who might dissent from a nuclear deal and who are possible swing players?
- What are the most controversial issues? Which actor inter-relationships do they stress?
- What issues have the potential to lead to factional realignments?

In November 2013, after the survey had been developed, an interim nuclear deal was announced between Iran and its negotiating counterpart, the P5+1 countries, consisting of the five permanent members of the UN Security Council (China, France, Russia, US, UK) and Germany. This spawned an additional question as to what may have caused the shift in Iran's posture toward nuclear negotiations which will be discussed in the section on simulation results. Space does not allow background on Iranian politics to be provided here – a good discussion of Iranian factional politics can be found in Rieffer-Flanagan (2013).

Analyst Survey

The analyst survey elicits expert judgment on the leadership group under study. The use of a survey methodology allows analysts to complete the survey at their convenience and avoids potential groupthink effects associated with oral elicitation of a group of analysts at one sitting. Only the Actor Opinions and Influence Network components of the survey are discussed here as they are the ones most essential for understanding the results presented below (other components are described in Gabbay (2013)). The surveys can be averaged to form a composite assessment or analyzed individually in order to bring out differences in analyst perspectives.

The Actor Opinions survey section contains a list of statements designed to assess the attitudes of the group members relevant to the policy issues of concern. For each member, analysts are asked to estimate the member's level of agreement/disagreement with a series of statements covering a range of issues, goals, identities, and specific policies. Examples include 'The production, stockpiling, and use of nuclear weapons are all forbidden in Islam' and 'The IRGC should play a guiding role in maintaining Iran as an Islamic republic'. The instructions direct analysts to score the statements on the basis of the private beliefs of the members if thought to be at odds with their public rhetoric. The Actor Opinions section is used to calculate member issue positions known as 'natural preferences,' a key parameter in both structural analysis and the simulation.

The Influence Network section contains a matrix in which analysts estimate the strength of each actor's direct influence upon each of the other members in the group and vice versa. This (directional) dyadic influence strength depends on factors such as the frequency of communications, status within the group, common or rival factional membership, and personal relationships of friendship or animosity. The influence network is used directly in structural analysis and to calculate the 'coupling strengths' which scale the persuasive force of one member on another in the social influence dynamics simulation.

Structural Analysis

Structural analysis involves quantitatively and visually probing the factional composition of the group as a whole and how individuals are situated within the group. Analyst judgments on discrete elements concerning individual actors and actor dyads are synthesized to enable the discovery of broader features and patterns in the group. In addition to being illuminating in its own right, structural analysis can help focus the simulation effort on particular issues such as those which are most polarizing or have the potential to result in new alignments of actor subgroups distinct from the dominant factional configuration. It also allows for insight into dynamics not encompassed by the simulation such as interactions between multiple issues, alliance formation, and succession considerations.

Issue Analysis

The methods for issue analysis utilize only the group member issue positions (natural preferences) calculated from the actor opinions. The analyses can address how contentious an issue is, how similar actor positions are for any given pair of issues, and patterns of actor alignment across the whole set of issues. This section presents examples of these analyses for the Iran case.

The most fundamental element of issue analysis is simply the actor natural preferences themselves as is shown in the plots of Figure 2. The positive end of the scale indicates support or a favorable attitude with respect to the issue and has a maximum value of 2. Similarly, the negative axis signifies opposition or an unfavorable attitude. These plots are useful for visual inspection of individual actor positions and their distribution within an issue as well as examining clustering across issues. To better highlight clustering patterns and deviations from them, conservatives are identified as those actors having negative scores on the Liberalism plot and marked by solid gray circles; reformers have positive Liberalism scores and are marked by open squares. The Liberalism plot shows a bloc consisting of KHAM (the Supreme Leader), SOL, SAF, JAN, YAZ and JAL at the far negative end of the axis indicating strong opposition to political and cultural liberalization whereas ROU (the president), KHAT, MUS and SAN are found oppositely at the pro-liberalization side. This pattern of opposed clustering is repeated for other issues as well thereby leading to the interpretation of the former subgroup as a core conservative or hardline faction and the latter one as a core reformist or moderate (from a US/Western viewpoint) faction. Note that RAF is usually aligned with the reformists except on the Economic Reform issue towards which he is most opposed. A subgroup composed of LAR, QAL and ASG typically forms a conservative-leaning centrist bloc with Economic Reform again a notable exception. The level of disagreement over an issue is indicated by the amount of spread in the actor positions as can be quantified by standard deviation (see Table 2 below). Nuclear Weapons, in which the actor positions appear most compressed, is the least contentious issue by this measure.

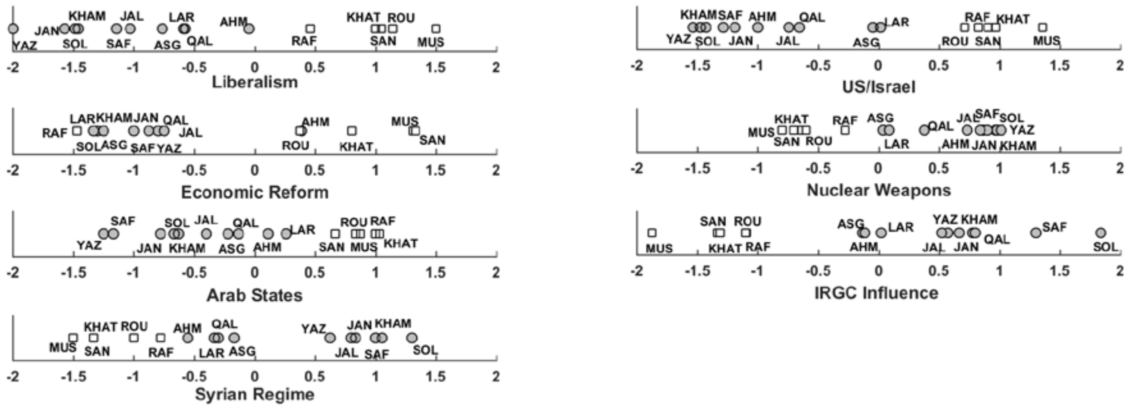


Figure 2. Actor natural preferences for the seven issues. Conservatives are gray circles, reformers are open squares.

To get a sense of the relationship between issues, Figure 3 shows plots of actor natural preferences on two pairs of issues. Observe in Figure 3(a) that the actor positions in the joint US/Israel and Nuclear Weapons space fall essentially on a line as is indicated by the almost perfect (anti-) correlation of -0.98. This implies that, although the issues are plotted on a two-dimensional plane, the system is essentially one-dimensional in the sense that if given the actor positions on one issue, then their positions on the second can be inferred with high accuracy. In Figure 3(b), Economic Reform appears on the vertical axis: there is now more scatter of actor positions and the correlation is lower in magnitude (although still highly statistically significant) indicating a less one-dimensional aspect. The core conservative and reform factions are still effectively at the opposite ends of the main axis (PC 1) but RAF and AHM are significantly off axis as are, to a lesser extent, ASG and LAR. The two plots have different implications with respect to potential coalitions if the two issues interact so that changing position on one issue affects an actor's position on the other. In Figure 3(b), RAF is nearer the conservatives and could side with them increasing his support for a more robust nuclear capability and bolstering their opposition to economic reforms. An analogous implication holds for AHM with respect to the reformist faction. Such realignment would not be possible if the two issues in play were US/Israel and Nuclear Weapons as in Figure 3(a): RAF would remain close to the reformers and AHM to the conservatives. However, it could be possible for ASG and LAR to be forced to side with one of the main factions if maintaining their centrist positions were to become untenable.

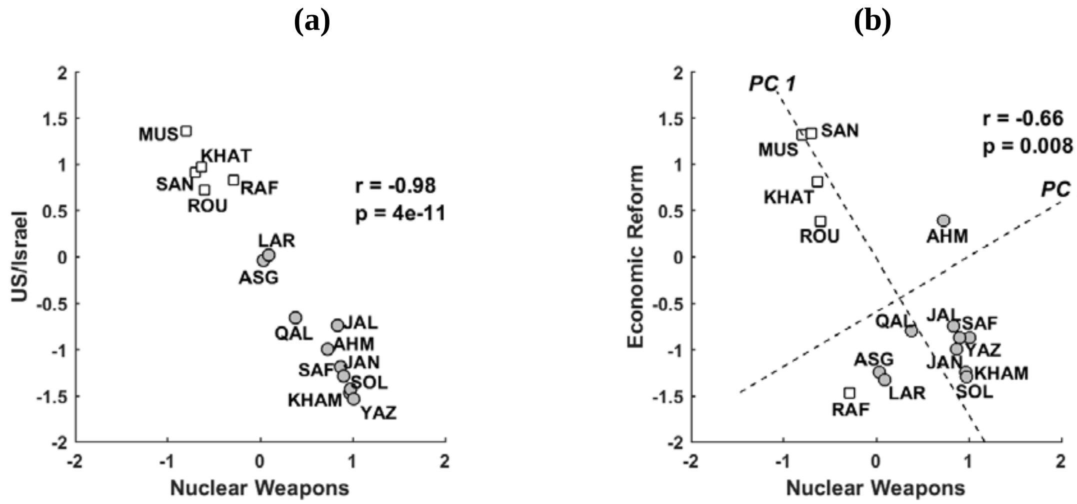
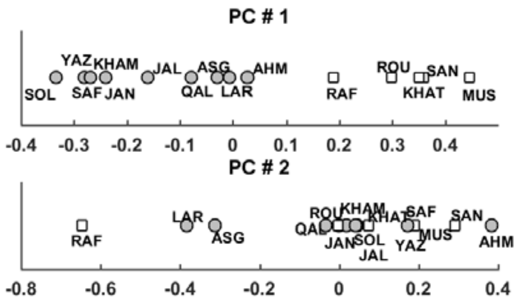


Figure 3. Two-dimensional issue plots: (a) US/Israel and (b) Economic Reform plotted vs Nuclear Weapons. The numbers in the upper right-hand corner are: the correlation between the actor positions on the two issues (*r*); and the p-value measure of statistical significance (*p*) which indicates the probability that the observed correlation could have occurred by chance given no underlying relationship – lower p-values imply stronger statistical significance. The dashed lines in (b) correspond to principal component axes.

While the discussion of factional alignments so far has involved visual inspection across issues, numerical methods exist for automatically revealing patterns of alignment. One such technique is Principal Components Analysis (PCA) which seeks to represent a data matrix by a series of coordinate vectors, known as principal components (PCs), each of which corresponds to a pattern of covariation in the data (Webb and Copsey, 2011). The PCs are ranked in descending order of importance as determined by how much of the variance (the data scatter around the mean) they carry which is given by their ‘eigenvalues’. Each PC is uncorrelated with the others so that they run as perpendicular directions through the data; in fact, they correspond to an alternative set of coordinate axes to the direct data variables.

For example, we can interpret Figure 3(b) as measurements of the two issue variables, Nuclear Weapons and Economic Reform, with each actor’s natural preference pair as a data point. The first PC then points in a direction along the dashed line running from upper left to lower right and the second is the line perpendicular to that. In essence, PCA has rotated the standard coordinate system, wherein each axis corresponds to one issue, to the dashed system where each PC is a weighted combination of the two issues (the weights can be negative). The origin is the intersection of the two PCs located at the point given by the mean along each issue. An actor’s coordinate on each PC is the (signed) distance between this origin and where he falls on the PC axis (the nearest point on that axis to him). The variance in the actor coordinates on PC 1 is given by its eigenvalue of 4.22 whereas PC 2’s eigenvalue is 1.75 so we see that PC 1’s share of the total variance (71 percent) is much larger than that of PC 2 (29 percent) indicating that PC 1 is more important in approximating the data. (The disparity between the two PCs would be even greater for Figure 3(a) given that it is much more one-dimensional.)



PC 1 Eigen-value	PC 1 Issue	PC 1 Issue Value	PC 2 Eigen-value	PC 2 Issue	PC 2 Issue Value
0.57	LIB	0.46	0.17	ECON	0.89
	IRGC	-0.44		USISR	-0.34
	USISR	0.41		ARAB	-0.26
	SYR	-0.39		NUKE	0.16
	ECON	0.32		IRGC	0.09
	ARAB	0.30		LIB	0.06
	NUKE	-0.28		SYR	0.03

Figure 4. First two principal components of actor natural preferences. Left: Actor coordinates. Right: Eigenvalues and issue values. Eigenvalues are expressed as the fraction of the total sum of eigenvalues. Issue values are listed in descending magnitude.

Turning to the complete set of issues, Figure 4 shows the first two (out of seven) principal components obtained from the data matrix formed by the natural preferences of each of the fifteen actors on all seven issues. The top plot on the left side shows the actor coordinates for the first principal component. This corresponds well to the dominant factional alignment identified in our discussion of the issue plots of Figure 2. The core conservative bloc of KHAM, SOL, SAF, JAN, YAZ and JAL is on the extreme negative end; the conservative-leaning centrists QAL, LAR and ASG are just left of zero and the core reform bloc of ROU, KHAT, MUS and SAN is on the far positive side. Rafsanjani is aligned with the reformers on PC 1 as is the case on six of the issue plots. Ahmadinejad’s location as a centrist may be surprising given his international reputation as a hardliner during his presidency but is supported by his position near the center or on the reform side for four of the issues. The eigenvalues in the corresponding table show that PC 1 carries 57 percent of the total variance, much larger than PC 2’s 17 percent share. This supports the interpretation of PC 1 as the dominant factional alignment. The PC 1 Issue Value column shows that there is no single primary issue whose magnitude is much larger than the others, again suggesting that PC 1 represents the most common pattern across the set of issues. This is not the case, however, for PC 2 where the Economic Reform component of 0.89 is by far the strongest. The plot of the PC 2 coordinates shows RAF and AHM at opposite ends reflecting the fact that, while the majority of the actors preserve the standard factional composition for Economic Reform, RAF and AHM make large against-the-grain shifts in the conservative and reformist directions respectively as observed in Figure 2 (RAF and AHM also appear at opposite ends of the second PC for the two-issue example of Figure 3(b)).

Network Analysis

Parallel to the investigation of issue-based factions described above, the factional structure which arises from the network of inter-actor influence relationships is also of concern.

Network science has developed many algorithms for detecting community structure in networks. Intuitively, the goal is to find subgroups of nodes which have more links among them than they do with other subgroups. Community structure may reflect similarities in preferences among network members via: the homophily principle (also known as assortative mixing), a formal construct for the commonplace that 'birds of a feather flock together' (Newman, 2010); or the mechanism of social influence which assumes that people who interact more often tend to become more similar (Friedkin and Johnsen, 2011). This section presents the application of a community structure algorithm which is then extended to illustrate how community structure and actor natural preferences can be integrated to address joint issue-network alignment.

The algorithm employed in PORTEND seeks to divide a network into two communities so that the network 'modularity' is maximized (Newman, 2006). The contribution to the total modularity from a given pair of nodes is proportional to the difference between their observed tie strength and that which would be expected if their interactions were solely due to chance; these contributions for all the dyads form the elements of the modularity matrix. The total modularity expresses the extent to which a putative division of the network into two communities exhibits a level of intra-community linking exceeding the level expected if the division were, in fact, arbitrary with no correspondence to behaviorally meaningful subgroups. The maximization is done in an approximate but efficient way by calculating the first eigenvector of the modularity matrix (eigenvectors are ranked in order of descending eigenvalue) and then assigning all nodes whose components in the first eigenvector are positive to one community and the nodes with negative components to the other. As an example, Newman (2006) presents an application to a network of 62 dolphins and finds that the two communities identified by the first eigenvector matched to high accuracy the two groups into which the network actually split after a key dolphin died (only three dolphins were misclassified).

The application of the community detection algorithm to the Iranian influence network is shown in Figure 5 which plots the actor coordinates obtained from the first two eigenvectors of the modularity matrix (using the symmetrized network in which tie strengths are the same in both directions in a dyad). We refer to the eigenvectors as 'factional dimensions'. The initial discussion of Figure 5 will center on the meaning of Factional Dimension (FD) 1 but, as will be seen below, FD 2 also has a significant interpretation regarding the Economic Reform issue. The dashed line corresponds to the division formed by separately grouping nodes with positive and negative signs in Eigenvector 1. The left and right sides correspond to conservative and reformer classifications respectively. The correspondence with the issue-based factions is immediately apparent because, as in PC 1 in Figure 4, all the gray circles are on one side and the white squares on the other. All members of the core conservative and reform blocs as identified by the issue analysis above are correctly classified. Only ASG can be considered to be misclassified as a reformer, perhaps understandable given that he is more of a centrist than a hardline conservative (and in fact he appears in the middle of FD 1).

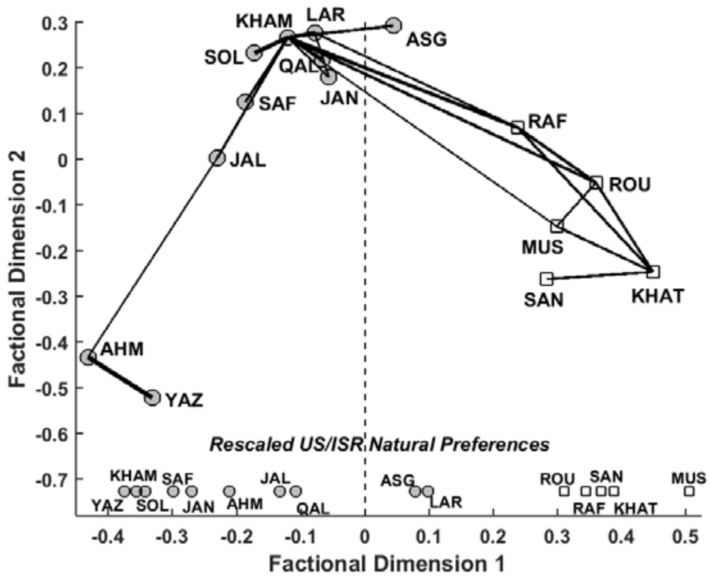


Figure 5. Community structure in the Iran influence network. Dashed line partitions network into conservative (left) and reformist (right) communities. Link thickness between actors is proportional to relationship strength (weak links have been thresholded). Points at bottom of plots are actor natural preferences for the US/Israel issue rescaled to fit inside the horizontal axis.

It is also possible to combine issue and network data for purposes of addressing polarization and factional realignment. As used here, polarization refers to the extent to which disagreement over an issue reinforces divisions present in the network. Hence, polarization is not simply the level of disagreement over an issue as might be gauged from the standard deviation of actor issue positions. Quantitatively, the contribution of an actor dyad to the polarization for a given issue is found by multiplying the corresponding modularity matrix element – network-derived data – by the product of the two actor natural preferences – issue data (which makes the polarization equivalent to the covariance between natural preferences over all the ties in the network (Newman, 2010)). The polarization value for each issue is shown in Table 2. For comparison purposes, the standard deviation of actor natural preferences is shown in the last column. The US/Israel issue is most polarizing even though Liberalism has the highest standard deviation. Nuclear Weapons and Economic Reform have very nearly the same polarization whereas the latter has a substantially larger standard deviation. Consequently, we see that the integration of network and issue data gives a different and perhaps more significant picture of issue divisiveness than issue data alone.

The Aligned Dimension column in Table 2 is the number of the factional dimension with which the issue has the highest magnitude correlation. The larger value of polarization of US/Israel as compared with Liberalism, despite the latter's higher standard deviation, is a reflection of the greater alignment that US/Israel has with FD 1 as seen by its better correlation in Table 2. A visual sense of this alignment can be gleaned from Figure 5 by comparing the actor network positions along the horizontal axis with their (rescaled) US/Israel natural preferences at the bottom. Whether or not the correlation represents a genuine relationship between the eigenvector and the actor natural preferences can be assessed from the p-value column with lower values indicating greater significance. All of the correlations in Table 2 are highly significant. Six of the seven issues best correlate with FD 1 reinforcing the conclusion that it represents the dominant factional division in the network. Consequently, these issues stress the major faultline in the group but are not likely to cause a fundamental factional realignment (although centrists may be forced to side with one camp or another as noted in connection with Figure 3(a)). However, Economic Reform is seen to align best with FD 2 (the vertical axis in Figure 5) and, therefore, if it were to become more salient, a factional realignment could be induced in which RAF allies more strongly with the conservatives and AHM does likewise with the reformers.

Issue	Polarization	Aligned Dimension	Correlation Magnitude	Standard Deviation
US/Israel	0.395	1	0.885***	1.036 (3)
IRGC Influence	0.393	1	0.779**	1.095 (2)
Liberalism	0.358	1	0.799**	1.142 (1)
Syrian Regime	0.248	1	0.731*	0.974 (5)
Economic Reform	0.198	2	0.645*	0.998 (4)
Nuclear Weapons	0.195	1	0.907***	0.701 (7)
Arab States	0.158	1	0.796**	0.786 (6)

Table 2. Integrated issue-network analysis metrics. Issues are listed in descending order of polarization. Statistical significance levels of correlations: * $p<.01$, ** $p<.001$, *** $p<.0001$. The last column shows the standard deviation of the actor natural preferences (rank in parentheses).

Nonlinear Social Influence Simulation

Model Description

The nonlinear model of social influence simulates the evolution of group member positions along the policy axis due to their mutual interactions. The social science underpinnings of the model derive primarily from social psychology theories of attitude change and small group dynamics and theories of foreign policy decision making (Eagly and Chaiken, 1993, Hermann et al., 2001). A brief summary of the model is presented in this section; fuller descriptions can be found in Gabbay (2007c, 2007b). It should be noted that since the model is focused on group dynamics, it does not involve a representation of the decision making calculus associated with particular policy choices (see Davis and O'Mahony (2013) for an example of a computational model that does so in the context of insurgent groups). With respect to other models of group dynamics, on a mathematical level, the nonlinear model is most similar to that of social influence network theory (Friedkin and Johnsen, 2011) to which the model can be made equivalent in the (linear) limit of low disagreement. The most prominent formal model of decision making applied to real-world political contexts is that of Bueno de Mesquita (1997, 2009) which however has received some criticism regarding lack of transparency (Scholz et al., 2011). While Bueno de Mesquita’s model uses analyst input and a one-dimensional issue axis as does the present model, it is based on expected utility theory whereas PORTEND is rooted in nonlinear dynamical systems theory and network science, cornerstones of complex systems research.

In the model, an actor’s position changes under the influence of two separate forces: the ‘self-bias force’ and the ‘group influence force’. Considering the self-bias force first, each actor is assumed to come to the debate with an initial issue position given by his natural preference (also called the natural bias) which reflects the actor's underlying beliefs, attitudes, and worldview pertinent to the issue. If an actor's position is shifted from his natural preference due to group pressures, he will experience a cognitive dissonance that resists this change and strives to move the actor's position back toward the natural preference.

The group influence force is the total force acting to change an actor's position due to the persuasive efforts of the other actors in the group. It is assumed to operate in a pairwise manner so that an actor – the message receiver – experiences a persuasive 'coupling force' from another actor – the message sender – to whom he is connected (and vice versa). The functional form of the coupling force is nonlinear in the difference between the sender and receiver positions: if the difference is small, the force increases roughly linearly; the force then reaches a peak at a difference known as the 'latitude of acceptance', beyond which it begins to wane towards zero. This form is motivated by social judgment theory which posits that the amount of opinion change in a person receiving a persuasive message follows an inverted U-curve as a function of the difference between the opinion advocated in the message and that of the receiver (Eagly and Chaiken, 1993) (however, the coupling force in the model has a long tail rather than ending abruptly as in an inverted-U). The coupling force that actor *j* exerts on actor *i* also depends on the 'coupling strength' from *j* to *i*, which is obtained from the influence network. The 'coupling scale' is the mean of the incoming coupling strengths (in-degree).

The model description above governs how actors change their positions under their mutual influence but does not yield the decision itself. In order to do so, the appropriate decision rule – leader choice, weighted majority, or consensus – must be applied. Typically, this is done after the simulation reaches equilibrium so that the actor positions reach steady-state values that no longer change perceptibly. For purposes of determining whether an actor supports or dissents from a policy decision, an actor is considered to support a policy if it lies within a specified maximum distance, usually taken to be the latitude of acceptance, from the actor's final position. Similarly, actors are taken to dissent from a policy if it lies beyond this distance.

Complexity enters into the model via the nonlinear form of the influence between actors and its interaction with the network formed by the inter-actor coupling strengths. The model can be considered to have two regimes of behavior: a 'linear' one, in which the behaviors typically correspond to initial intuition, and a 'nonlinear' regime corresponding to high disagreement (roughly, position differences exceeding twice the latitude of acceptance) in which behaviors can run counter to initial intuition. The linear regime is always characterized by gradual changes in outcomes as parameters such as the level of disagreement or coupling scale are varied whereas the nonlinear regime can exhibit discontinuous transitions, referred to as bifurcations, between states such as deadlock, majority rule, and consensus (Gabbay and Das, 2014). With respect to the interaction of nonlinearity and network structure, at high disagreement levels networks with lower tie density (for example, a chain) can be more effective at reducing group discord and yielding consensus than ones with higher density (for example, a complete network) in contrast with the 'linear' expectation that a higher number of ties is better for consensus formation (Gabbay, 2007b).

Simulation Results

All seven issues were simulated. Here only the Nuclear Weapons results are discussed as that issue was of primary analytical concern. The simulation using the set of parameter values calculated directly from the composite analyst is shown in Figure 6(a). The latitude of acceptance is taken to be one unit along the issue axis as that corresponds to a step along the attitude survey scale, say from ‘neutral’ to ‘weak agreement’ or from ‘weak agreement’ to ‘strong agreement’. Actors start out at their natural preferences and the time units are essentially arbitrary given that the equilibrium is of concern.

The policy labels and corresponding intervals in Figure 6(a) are calculated from the Actor Opinions section of the survey (they can also be set manually) and are intended to be rough guides to assist in interpretation of simulation results rather than hard and fast boundaries. The Weapons Capability policy corresponds to an actor believing that a nuclear weapons capability is critical to ensuring the survival of the Iranian regime. Breakout signifies that the actor prefers that Iran should have the ability to develop nuclear weapons without building or testing them. Strong Restrictions signifies that the actor is willing to accept more forceful constraints on Iran’s nuclear enrichment program such as intrusive monitoring of nuclear facilities in exchange for the removal of economic sanctions (a fourth policy of No Enrichment was not preferred by any actor).

The decision rule is leader choice and the open diamond indicates the final policy, coincident with KHAM’s final position. We see that the policy choice is located in the Weapons Capability zone, justly slightly less hardline than KHAM’s initial natural preference. This is not surprising given the outsize influence that KHAM has on the group; his network out-degree – the sum of all his outgoing influence network values on the rest of the group is more than three times the second highest actor. Rafsanjani does move sufficiently towards a harder line so that he can support the policy. However, the core reformers, most notably ROU, dissent as they end up greater than one unit (the latitude of acceptance) from the policy.

The above result, however, is inconsistent with the more conciliatory posture that Iran took in reaching the interim nuclear agreement in November 2013. It is not tenable that the Iranian president Rouhani, a savvy political insider, would have been vigorously pursuing a nuclear deal with the United States completely at odds with the Supreme Leader’s policy, thereby setting himself up for failure. This leads to the inference that the Iranian policy may have shifted to a softer line than represented in the original analyst data. Possible scenarios underlying this shift can be investigated by changing the simulation parameters. Simulations of scenarios involving increased group cohesion or increased reformer status due to Rouhani’s election in June 2013 could not produce a significant enough policy shift. But another potential explanation is that Khamenei himself softened his position, which can be modeled by shifting his natural preference in the negative direction along the Nuclear Weapons issue axis. This can indeed account for the softer line policy: given the leader choice decision rule and his great influence, the policy essentially follows his natural preference; a shift of -0.2 brings the policy into the Breakout range and a shift of -1 moves it into the Strong Restrictions range.

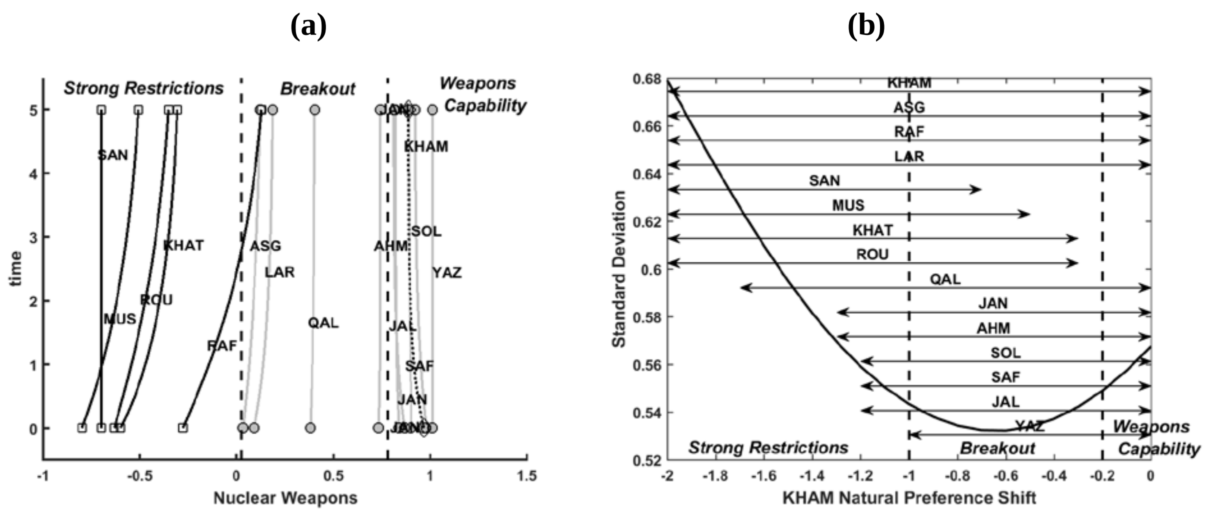


Figure 6. Nuclear Weapons issue simulation. (a) Actor trajectories using composite analyst values (first letter of actor abbreviation intersects with trajectory curve). Dashed lines demarcate boundaries between different policy labels. Dotted line is policy value (same as KHAM trajectory due to leader choice rule) and open diamond at top is policy decision. (b) Effect of Khamenei softening his natural preference: standard deviation of actor final positions (solid curve) and actor concurrence intervals (double-headed arrows, actor listed above). Horizontal axis is shift from KHAM original natural preference from composite analyst.

While it is clear that Khamenei can shift the policy if desired, considerations of minimizing discord within the leadership as a whole and, in particular, maintaining the support of key hardliners – the IRGC members Soleimani and Safavi, and Janati, the chairman of the Guardian Council – are doubtlessly important in his decision making calculus. These factors can be assessed using Figure 6(b) which plots the standard deviation of the final positions and the concurrence interval for each actor – the range of KHAM's natural preference shift over which the actor supports the policy decision. Observe that there is a minimum in the standard deviation at a shift of about -0.6 approximately in the middle of the Breakout interval (the fact that the curve has a minimum rather than simply monotonically increasing or decreasing stems from the nonlinear nature of the model). Furthermore, there is a range from about -0.7 to -1 for which all actors concur with a policy in the Breakout zone. These observations imply that a Breakout policy would minimize discord within the group. Indeed, as KHAM moves into the Strong Restrictions zone, he rapidly begins to lose conservative support: first YAZ, then crucially at -1.2 the IRGC members SOL and SAF, followed shortly thereafter by JAN.

The above analysis leads to the conclusion that the Khamenei softening scenario is a plausible explanation for Iran's shift to a posture more amenable to reaching a deal on the nuclear issue; he can maintain consensus while pursuing a Breakout policy, which is consistent with trying to reach a nuclear agreement, albeit one which would be very weak from the perspective of the United States. The fact that there were secret meetings between US and Iranian officials on the nuclear issue starting in 2012, a year prior to Rouhani's election (Associated Press, 2014), suggests that Khamenei may very well have shifted towards a more flexible position than the original hardline Weapons Capability ascribed to him from the analyst surveys. With respect to the prospects of reaching a final deal, his original analyst-derived position would imply that a deal would be extremely unlikely. The analysis of the softening scenario indicates that Khamenei's room for maneuver is limited so that he can only move a small amount into the Strong Restrictions zone before losing the support of key conservatives. This suggests that a deal which provides robust provisions against an Iranian breakout capability – in particular, the US stated that it sought a minimum breakout time of one year – would indeed be possible but very difficult to reach. A deal between Iran and the P5+1 was in fact announced in July 2015. An assessment as to the strength of the deal from the P5+1 perspective – whether the monitoring and other restrictions on Iranian nuclear activities are sufficiently robust as to prevent a rapid breakout capability or a covert program – cannot be made here. However, the fact that the negotiations took twenty months from when the interim deal was announced to reach a final agreement, including two six-month extensions of the interim deal, attests to the difficulty in consummating the negotiations.

Conclusion

Relationships among leadership elites and their preferences on important issues are essential elements in determining the outcomes of policy debates. This chapter has presented a methodology, implemented with the PORTEND software package, for the analysis of the factional structure of leadership elites and the simulation of their group decision making via the nonlinear social influence model. Methods for investigating factional structure based on issue data alone range from simple standard deviations and plots of actor natural preferences to more sophisticated pattern extraction using Principal Components Analysis, which revealed meaningful dominant and subordinate factional alignments among the set of Iranian leaders; the first corresponding to the primary conservative-reformer divide over most of the issues and the second reflecting key departures from this alignment with respect to economic reform. Complementary to the issue analysis, the application of a community structure algorithm to the inter-actor influence network also yielded similar dominant and subordinate structures via the first two eigenvectors. The uncovering of the parallel structure in the issue and network data illustrates the power of applying methods from research in complex networks. This research also forms the basis for the polarization metric which quantifies the extent to which differences in actor issue positions also stress network faultlines, thereby providing an integrated measure of how divisive an issue is.

The social influence model entails complexity via its nonlinear coupling of actors over their influence network and was applied to Iranian nuclear decision making. Simulation of the original analyst values yielded a policy decision that was so hardline as to be inconsistent with apparent Iranian moves towards more negotiating flexibility in late 2013. The model's capability for scenario analysis was illustrated to address this inconsistency. Khamenei's shift towards a more moderate natural preference was found to be the most plausible explanation. Sweeping over his natural preference shift, the simulation indicated that he had sufficient room to maneuver before losing the support of key hardliners so as to make negotiations tenable. However, his ability to enter the Strong Restrictions zone, which presumably would have considerable overlap with the goals of the P5+1 countries, was found to be quite limited implying that achieving an agreement would be quite difficult – a conclusion perhaps supported by the long period of time required to reach a deal.

Finally, addressing further research, one area could involve the investigation of whether automated content analysis of actor rhetoric could be a viable input source for either the structural analysis or the simulation. Another area could be extending the social influence model to a multidimensional issue space in order to allow issues to trade off against each other.

Additionally, complexity research on adaptive networks could be used to develop an issue-network coevolution model in which both issue positions and network ties would interact and change dynamically, thereby explicitly modeling alliance formation processes, a capability not present in the current model.

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Appendix 4

Ideology, Identity and Militant Group Networks in Iraq

IDEOLOGY, IDENTITY, AND MILITANT GROUP NETWORKS IN IRAQ

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INTRODUCTION

Research using social network analysis to study terrorism and insurgency increased dramatically following the 9/11 attacks against the United States. This research emphasizes the importance of relational analysis and provides a variety of concepts, theories, and analytical tools to better understand questions related to militant group behavior and outcomes of terrorism and insurgent violence. The main focus of this research has been on organizational analysis and its implications for militant group operational processes and performance. However, few studies have investigated how differences in network structure lead to divergent outcomes with respect to political processes such as militant group infighting, their strategic use of violence, or how politically salient variables affect the evolution of militant cooperative networks (Zech and Gabbay 2016). Scholars can use network analysis tools to investigate the political interactions of militant groups during intrastate conflicts and focus on specific issues such as infighting, alliance formation, or outbidding. These types of studies will be of particular value in advancing our understanding of fragmented civil wars and insurgencies consisting of multiple, independent militant groups.

In this paper we use network analysis tools to examine militant group alliances and cooperation in Iraq. We argue that how groups frame political goals and define which actors constitute legitimate targets for violence will affect militant group cooperation and alliance formation. To evaluate the argument we identify the broader conflict frame for each militant group and use thousands of translated statements to generate quantitative measures for militant group ideology and identity. We then use these variables to investigate patterns in relationships for two distinct networks – joint operations and joint leadership statements – across three time periods during the Iraqi insurgency. Our findings support the proposition that militant group ideologies and identities affect alliance and cooperation with other militant groups.

Our research makes two important contributions to research on insurgent alliance formation and cooperation, as well as the field of security studies more broadly. First, our methodological approach provides a novel way to examine relationships and to quantitatively measure militant group identity and beliefs about violent action. These methods and data provide insight into why militant actors use violence differently, leading to a more nuanced evaluation of militant group preferences and behavior. Furthermore, network analysis is the most appropriate tool for investigating questions about relational outcomes. Researchers who investigate alliances, cooperation, the diffusion of ideas or resources, and other interaction outcomes will benefit from network analysis tools that can model relationships and that generate additional metrics to capture systemic features.

Second, our study makes important theoretical contributions. Many explanations for insurgent alliances have been proposed. Some build on a rationalist bargaining framework, while others have probed the limits of that approach and suggested alternative explanations such as elite networks and ethnic cleavages. Existing studies often refer to vertical or horizontal networks, alignments, factionalization, and other relational characterizations, yet comparatively few explicitly engage with network analysis. This study proposes a model that treats the overall network of militant group ties as the object of interest, wherein ideology and identity affect the overall alignment of groups.

MILITANT GROUP DYNAMICS: ALLIANCE FORMATION AND MOVEMENT FRAGMENTATION

Two principal lines of research investigate group-level militant relationships. The first examines intra-conflict group alliances. The second considers fragmentation or splintering, a process that describes when different factional elements of a group break off to form their own competing organizations. Within those categories scholars have proposed numerous factors that can motivate or inhibit alliance and cooperation. We investigate the role of policy preference and identity in greater detail to better understand the process of cooperation. A group's use of violence and its political values can constitute indivisible, irreconcilable differences that hinder cooperation or they can signal shared characteristics and goals that invite the potential for alliance.

Alliance Formation

Alliances between two or more actors indicate some degree of commitment, expectation, or obligation between them. These cooperative arrangements matter when they affect decision-making or when they alter perceptions (Morrow 2000). They also provide an opportunity to signal to other actors; indicating stronger commitments, greater coordination capabilities with allies, or increased audience costs (Fearon 1997). While the majority of alliance research focuses on international relations and alliances between states, newer research examines how groups cooperate and form coalitions in civil war. Understanding what factors explain militant group alliances and cooperation matters because they affect organizational capacity and the lethality of attacks (Horowitz and Potter 2014). There are limits to borrowing from theories of interstate alliances. Militant alliances during complex conflicts tend toward fluidity and informal commitments rather than codified legal obligations.

Absent enforceable agreements, credible commitments become a significant factor for determining rebel cooperation. Militants use group type or organizational characteristics as cues to judge potential partners (Furtado 2007). Christia (2008) argues that alliances reflect relative power considerations; groups' political identities are formed *ex post* in order to justify new alliances. External sponsorship can upset the balance of power, or mediate between competing factions, while susceptibility to government repression influences a group's decision to seek allies (Bapat and Bond 2012). Identity and reputation have a role in some of the bargaining literature to the extent that it can provide insight into another actor's credibility and incentives to defect from cooperation (Bond 2010).[1]

Movement Fragmentation

The introductory article to a 2012 special issue of the *Journal of Conflict Resolution* points to some limitations of a bargaining approach to militant factions, particularly the assumption that such groups constitute stable, unitary actors (Pearlman and Cunningham 2010). The authors note that shifting coalitions influence collective behavior and subsequent outcomes: "[E]ven in a single ethnic group, where it is assumed that a powerful identity effectively binds individuals together, there is often a dizzying diversity of political strategies and organizational forms" (2012, 4). For example, ethnic militias, frequently treated as unitary, are often internally divided and ethnicity may not be a simple marker term for denoting organizational stability. Lethal competition between co-ethnics can lead to

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[1] Bond measures her identity label as the type of violence that an organization employs (indicating a reputation for resolve), its history for having cooperated or not (indicating a reputation for being committed to cooperation), and its ideological affiliation (indicating its motivational principles) (2010, 38-44).

factional defections wherein some elements of an ethnic movement split and realign themselves with the government (Staniland 2012). Where ethno-political organizations have factionalized leadership structures, and disagree about appropriate levels of violence, they are more likely to split (Asal et al. 2012). McLauchlin and Pearlman (2012) find that intra-movement cooperation depends on subgroup satisfaction with pre-existing cooperative arrangements that distribute power and resources.

Other studies examine fragmentation as an independent variable to assess how it affects outcomes such as violence or state-building. Cunningham et al. (2012) develop a "dual contest" framework to argue that inter-factional competition within divided movements leads to *more* violence. However, Driscoll (2012) finds that in Tajikstan fragmented groups led by warlords respond to incentives offered by the state and suggests that fragmentation can facilitate conflict resolution, thus leading to *less* violence. Scholars that study fragmentation focus on organizations pursuing collective interests fundamentally tied to a particular identity, recognizing that multiple organizations within a single movement may disagree about what those interests are and the appropriate means to pursue them (Bakke et al. 2012). Yet, few models expressly account for identification categories, different ideas about how to best accomplish political objectives, or how groups cast themselves in relation to other actors.

Intra-group Dynamics

A spatial politics approach can provide insight into shifting militant group relations. In this paper militant groups take the place of political parties. They interact in different ways and, for example, might form temporary coalitions on the basis of their proximity in a policy space. The case of Iraq presents an interesting puzzle: why did the array of nationalist groups not consolidate into a coherent power block given that their common political goals of a unitary, territorially intact Iraq with a basis in Islamic law? Observed behavior runs contrary to prevalent theories of insurgent alliance formation that would expect groups to consolidate to form winning coalitions.

Most organizational studies of militant behavior do not look closely at variation in policy preferences among groups or their multi-level nature. We characterize the groups in Iraq as two-level organizations with a relatively static leadership cadre and a more fluid collection of soldiers. One potential explanation for the failure of Iraqi nationalist groups to form a unified front lies in the commitment problem created by their power relationships (Fearon 1995; Powell 2006; Walter 1997, 1999, 2004). However, commitment problems as an explanation for war-inefficiency are not well-suited to explain both the cooperative behavior at the rank-and-file level and close leadership ties. In fact, the common leadership-level goal of a unitary Iraq with a place at the table for all sects and ethnicities implies that, at a minimum, nationalist groups should have been able to unite against the proliferation of jihadi groups and foreign fighters. In an alternative context, Ramadi tribal sheikhs were able to create a sustained coalition against Al-Qaeda in Iraq which lasted, in one form or another, for nearly eight years. The logic of commitment problems between militant groups also implies that once they commit to fighting, they should be unable to credibly commitment to alliances with one another. Yet, Iraq's civil war was not a true fight to the finish, rather it ended with a pseudo-federated, multi-ethnic state under an elected central government. The competing sides were somehow able to overcome commitment problems and reach a negotiated, albeit troubled and sectarian, settlement.[2] In the following section we develop an alternative framework for understanding sectarian conflict in Iraq based on groups' (dis)agreements over conflict frames and how they viewed themselves in relation to other collective actors.

THEORETICAL FRAMEWORK

[2] Among the interesting features of the Iraq settlement deal is that the various warring factions were, in fact, allowed to maintain autonomous armed forces while many others were folded into the Iraqi national army. The commitment problems argument generally highlights the insecurity of formerly armed groups as a major barrier to peace.

Ideology and Identity

We suspect that militant group ideologies and identities affect the likelihood of alliance and cooperation between groups. Competing ideologies and identities foster political competition and can prevent alliances and cooperation between groups, especially within the same conflict. Alternatively, shared ideological orientations and common enemies, among other factors, can foster alliances between militant groups (Bacon 2014, 2015; Asal et al. 2016).[3] Despite some acknowledgment of the importance of ideology and identity, existing research on militant group alliance and cooperation overwhelmingly emphasizes a bargaining model framework. Although many recognize that a broad range of non-instrumental motivational factors drive decision-making and behavior, scholars have not performed adequate empirical analyses.[4] To understand when and how militant groups form alliances and cooperate with other groups, we must explore a broader range of potential explanations in a systematic way using better data.

Militant Group Ideology

What is ideology and how might it affect militant group behavior? Malcolm B. Hamilton proposes a relatively concise definition for ideology based on over two-dozen conceptual elements he identifies in a review of the literature:

> An ideology is a system of collectively held normative and reputedly factual ideas and beliefs and attitudes advocating a particular pattern of social relationships and arrangements, and/or aimed at justifying a particular pattern of conduct, which its proponents seek to promote, realise, pursue or maintain (1987, 38).

Gerring (1997) also reviews academic literature on the ideology concept and finds a range of definitions across the social sciences. Despite the term's "semantic promiscuity," he finds numerous threads linking diverse conceptualizations. Ideology provides a collective interpretation of social fact, or how groups come to see the world. Group ideology provides a frame of reference that prioritizes particular ideas, beliefs, and values as people formulate strategies of action. Ideology structures both relationships and conduct. In other words, ideologies consist of and communicate a shared understanding of the world and specify the acceptable means to achieving social, economic, and political ideals (Jost, Federico, and Napier 2009, 309).

Ideologies influence group behavior during armed conflict. They identify constituencies, clarify group objectives, and prescribe programs of action. Ideologies can enable or constrain decisions based on both instrumental calculations and normative commitments (Gutiérrez Sanín and Wood 2014). Ideologies influence all parties to armed conflict including states, civilian militias, and militant groups. For example, Staniland (2015) finds regime ideology to play a crucial role in explaining how governments perceive and deal with militias. He observes, "Identifying who is—and is not—a potential ally is rarely an obvious calculation, and it varies across governments and over time within them. There is a deeper ideological politics at work that influences both which regimes are open to using militias and which kinds of groups are seen as potential partners" (2015, 771).

Ideological considerations also affect how states apply force through the traditional military and security services during armed conflict. For example, in Latin America from the 1960s through the 1990s, many governments targeted political opponents from the ideological Left. "Dirty Wars" in Argentina, Chile, Peru, and elsewhere entailed widespread torture, disappearances, and human rights abuses. During "Operation Condor," states in the Southern Cone of Latin America developed an international intelligence and operations network to target ideological opponents. Leftists, dissidents, union and peasant leaders, clergy, intellectuals, students, and suspected guerrillas faced anti-democratic

[3] Note that existing studies focus on cross-national terrorist group alliances and not cooperation within a single conflict.

[4] A notable exception would be an excellent piece on defections ("side switching") in Sudan. Seymour (2014) finds access to resources and political rivalries to play a greater role in group decisions than identity and ideology.

and messianic officers bent on eliminating the perceived threats of communism, subversion, and even peaceful movements for social change (McSherry 2002). One cannot investigate armed conflict apart from ideology.

Ideology is also essential for understanding militant groups. For example, many participants in the Revolutionary Armed Forces of Colombia (FARC) forewent material gains and maintained a strong commitment to personal sacrifice based on their revolutionary ideology (Gutiérrez Sanín 2004). Ideology can help explain sustained FARC participation or defection. Survey research on ex-combatants suggests those who joined for ideological reasons were less likely to defect than those that did not, though they were more likely to switch sides if they perceived their group had strayed from its original ideological precepts (Oppenheim, Steele, Vargas, and Weintraub 2015). The maintenance or erosion of particular ideologies will affect violence during armed conflict, as can be seen in cases like Mozambique and Angola (Thaler 2012). In worst case scenarios ideology can facilitate mass atrocity (Leader Maynard 2014). Alternatively, transforming elements of particular ideologies can become a key component in conflict resolution and achieving sustained peace (Todd 2010).

As sociologist William H. Sewell Jr. reasons, "…ideologies inform the structure of institutions, the nature of social cooperation and conflict, and the attitudes and predispositions of the population. All social relations are at the same time ideological relations, and all explicit ideological discourse is a form of social action" (1985, 61). For Sewell, ideologies are ever-present, indispensible components of social life that structure behavior. Militant groups articulate elements of ideology within their conflict frames and we suspect that ideological similarities and differences will affect whether militant groups form alliances and cooperate. In his study on insurgent cohesion and collapse Paul Staniland identifies ideology as a key obstacle for militant groups that wish to embed within local populations, "Local alliances do not occur when the insurgency is ideologically rigid in its beliefs about how local social and political life should be structured and unwilling to accommodate local norms and interests" (2014, 45). This logic should extend to inter-group alliances. Militants who show similar beliefs and attitudes will find it easier to work together and their preferences are more likely to align. Hypothesis 1 (H1) predicts that if militant groups share similar ideologies, then alliances and cooperation are more likely.

Militant Group Identity

Identities are notions of how groups see themselves in relation to others, along with appropriate behaviors given those beliefs. How actors understand themselves and others influences group behavior (Turner 1982; Abrams and Hogg 1990; Laitin 1998). Group identities are not static categories. As Abdelal, Herrera, Johnston, and McDermott suggest, "Individuals are continuously proposing and shaping the meanings of the groups to which they belong" (2006, 700). We describe to others what we are and what we are not. Identities include relational elements along with beliefs about the boundaries of inclusion or inclusion. The potential for conflict or cooperation often takes place around this boundary (Tilly 2002; Tilly 2005).

Militant group identities can lead to conflict and facilitate violence. Social identities such as ethnicity can lead to violence in a variety of contexts. Identities are both a cause and consequence of violence, evolving throughout a conflict (Fearon and Laitin, 2000; Kalyvas 2006; 2009). They can influence decisions about the targets and nature of violence. For example, throughout the guerrilla conflict in Missouri during the American Civil War, while the mutilation and killing of male enemy soldiers became quite common, "Conversely, there was a concomitant, rigorously observed ban on raping, killing, or mutilating white women" (Fellman 1989, 189). Republican soldiers exhibited similar restraint during the Spanish Civil War where, despite widespread clerical violence targeting Catholic priests, they did not target nuns (Vincent 2005). Identities and the associated norms that constitute legitimate and appropriate behaviors influence if, and how, armed actors use violence.

However, identities do not lead uniformly to violent conflict. As Ted Hopf explains, "Identities are always relational, but only sometimes oppositional" (2002, 7). For example, Protestants in Northern Ireland experienced a clear shift in the content of their British identity, the way they understood their relationship with the Irish state, and what that meant for post-conflict politics (Mitchell and Todd 2007). Changing identities can move groups toward or away from violence. Armed groups continually redefine their relationships with other groups during conflict and this process affects subsequent strategies and behavior (Zech 2016). The way a group views the potential for, and desirability of, violence against others will also influence the group's network of partners. In Iraq, Sunni militant organizations exhibited variation in how they saw themselves in relation to others and adopted different targeting policies over time based on varying beliefs about which other actors were legitimate targets of violence (Gabbay and Thirkill-Mackelprang 2011). We predict that group identities will influence decisions about alliance and cooperation over time. Hypothesis 2 (H2) predicts that if militant groups share similar identities, then alliances and cooperation are more likely.

RESEARCH DESIGN

In this paper we argue that ideology and identity help explain militant group alliances and cooperation. To test the argument we analyze relational and attribute data from Sunni militant groups in Iraq between 2003 and 2009. We use militant rhetoric as data and network analysis tools to assess the relationship between ideology, identity, and militant group alliance and cooperation. This study examines two outcomes: 1) leadership alliances and 2) cooperation at the operational foot-soldier level across militant groups. Research on group dynamics suggests that within groups, actors adopt particular roles and individual actors hold varying levels of influence based on power, status, or prestige (Knippenberg and Hogg 2003). When a group interacts with another group, many actors will look to leadership figures within their own group for guidance concerning the best or most appropriate course of action. Intra-group dynamics affect inter-group relations. Accordingly we consider both the less formalized cooperation between foot-soldiers and the more formalized network of joint cooperative statements between leaders. In the following section we describe the dataset and present a framework for modeling the dynamic patterns of militant group ties.

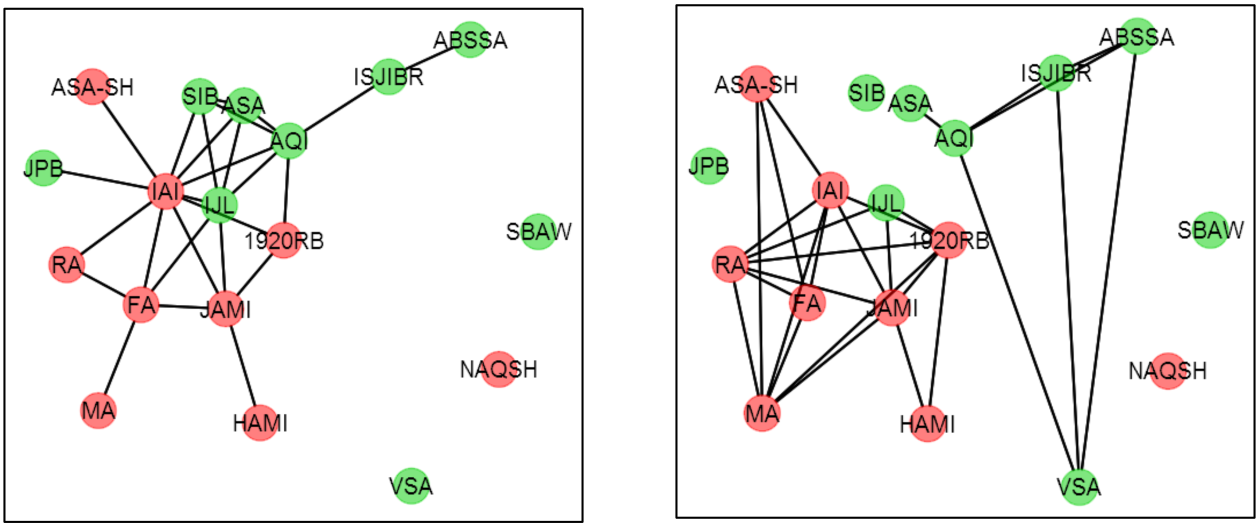
Data

This study uses an original dataset constructed from the U.S. government's Open Source Center. The dataset uses translated statements from interviews, print media, broadcasts, and websites to construct relational and attribute variables for Sunni militant groups in Iraq over three time periods. The unit of analysis is at the group level. We evaluate leadership joint statement networks and foot-soldier joint operations networks in Iraq from 2003-2005, 2005-2007, and 2007-2009 using undirected, valued ties for each time period. These time periods correspond to a slow-building surge and subsequent waning in sectarian violence. In the first period, Sunni militant groups began to form and exhibit defined group structure as they resisted U.S. occupation. Sectarian violence increased dramatically by 2005 before subsiding rapidly through 2007. Thus our time periods capture the early, uncertain period of the insurgency, the period of intense sectarian conflict, and the period after the 2007 troop surge and U.S. campaign against Al-Qaeda in Mesopotamia. Not all groups existed in each time period. As shown in Table 1, time period 1, t1, is the sparsest, with nine observed groups, t2 contains eighteen groups, and t3 includes sixteen groups.

The dependent variables: leadership alliances and foot-soldier cooperation networks

The dependent variables capture factional structure among Sunni militant groups in Iraq. We identify leadership alliances through joint communiqués; statements issued by two or more militant factions. This measure is designed to assess public cooperation among the central leadership or the administrative apparatus of insurgent factions. We identify foot-soldier cooperation through joint operations. These actions are captured through claims of tactical coordination at the local level between groups of soldiers. We measure militant group alliance and cooperation as relational network data as shown in Figure 1 below.

Figure 1: Joint leadership alliances (L) and foot-soldier cooperation (R) in the 2005-2007 time period. Green triangle nodes are Jihadist groups and red circles are nationalist.



The independent variables: ideology and identity

We argue that ideology and identity will affect militant group alliance and cooperation. We use two measures to examine militant group ideology. First, we classify each group as Nationalist or Jihadist Salafist (henceforth "Jihadist")—two broad categories scholars use to describe insurgent factions in Iraq. These broader categories capture many of the prevalent goals, strategies, and beliefs of the various militant groups (Hashim 2005, 2009; Hafez 2007). Jihadist groups strive to establish a pan-Islamic caliphate and advocate adherence to a strict, orthodox interpretation of Islamic law. Jihadists also express overt hostility toward Shiite groups, fueling sectarian tensions. The two principle Jihadist groups at the height of the Iraqi insurgency include Al-Qaeda in Iraq and Ansar al-Sunnah (which later reverted back to its original name, Ansar al-Islam). In contrast, Nationalist groups seek a united Iraq with less emphasis on anti-Shiite rhetoric. They seek to maintain the geographic and demographic integrity of Iraq and prefer a strong central government to a federal one. Nationalists are also Islamist and seek to establish a state that adheres to Islamic law, but Nationalist groups see a place for Shiites and other ethnic groups and sects within a new Iraq.

Second, we generate a conflict frame measure for ideology based on the frequency that militant groups use marker terms. These rhetoric-based terms capture valued statements about in- and out-group politics. For example, claims of attacks against 'foreign occupiers' or the 'puppet regime' would be coded as negative statements directed against US forces and the Iraqi government. We normalize these frequencies into two measures that capture 'resistance' and 'sectarian' master frames and position groups in a frame-space of resistance-sectarian beliefs. These conflict frames identify a group's enemies and circumscribe its potential allies. Resistance frames generally emphasize a U.S. versus Iraqi focus and sectarian frames generally emphasize a Sunni versus Shiite focus. The resistance and sectarian frames are negatively correlated – groups that claim sectarian values and identification do not tend to emphasize resistance, while those that organize around resistance (to occupation or illegitimate government forces) largely eschew sectarian competition.

We measure identity with a militant group targeting policy metric. Targeting policy captures group claims about violent action. This relational measure indicates the legitimacy of target classes for different groups of actors during each time period. Targeting policy captures the dynamic nature of identity as groups continually redefine how their group stands in relation to other important collective actors in the conflict. Disagreements over legitimate targets of violence has been a major source of dissension within Islamist insurgencies (Hafez 2003). We construct the targeting policy measure with group targeting attitudes ranging from -2, forbidden or strongly disapproved, to +2, explicitly claimed. We assess fourteen target classes.[5] After determining the legitimacy score for each target we calculate the average of its values for the entire group ensemble. Each group's targeting policy is the average legitimacy of the targeting classes it explicitly claims. Thus a group whose portfolio includes targets that are considered less legitimate within the context of the insurgency will receive a lower score than a group that primarily targets coalition forces. Higher scores indicate a more discriminating, selective use of violence; lower scores correspond to more controversial targeting that is viewed as less legitimate by other groups on average. Because the overall target class legitimacy is a product of all groups' statements, an individual militant group's targeting policy value can change over time even if its actual claims do not.[6] We note that all groups claim foreign/coalition forces as legitimate through all time periods but foreign civilians drop off after 2005 when many groups began to shift their strategies to coincide with long-term strategies and adopt a more professionalized militant image. Groups also shifted targeting policies toward Shiite militias as sectarian violence intensified between 2005 and 2007. Distance on the targeting policy scale can be thought of as disagreement over the legitimate use of force—groups with low values are more willing to use force against any targets, while high values indicate selectivity (Gabbay and Thirkill-Mackelprang 2011). Table 1 shows the militant groups in our analyses along with metrics that capture group ideologies and identities over time.

Table 1: Militant groups, ideologies, and identities in Iraq 2003-2009.

Group	Classification	Sectarian Frame			Targeting Policy		
		2003-2005	2005-2007	2007-2009	2003-2005	2005-2007	2007-2009
1920 Revolution Brigades (1920RB)	Nationalist	0.08	0.12	0.05	1.33	1.67	1.94
Abu Bakr al-Siddiq Salafi Army (ABSSA)	Jihadist	-	0.45	0.4	-	1.54	1.11
Al-Qaida in Iraq (AQI)	Jihadist	0.36	0.49	0.5	0.77	0.66	0.64
ASA (ASA)	Jihadist	0.37	0.52	0.48	0.89	0.99	1.08
Ansar al-Sunnah Shariah Commission (ASA-SH)	Nationalist	-	0.37	0.35	-	2	1.61
Fatihin Army (FA)	Nationalist	-	0.37	0.31	-	1.26	1.38
HAMAS-Iraq (HAMI)	Nationalist	-	0.06	0.1	-	1.78	1.81

[5] The target classes are: US forces, foreign civilians, Shiite militias, Kurdish militias, Iraqi government forces, police, spies/agents, Iraqi government civilians, politicians, Sunni local leaders, Shiite civilians, Sunni civilians, oil pipelines, and Sunni militias.

[6] These data are described in detail in Gabbay and Thirkill-Mackelprang (2011).

Islamic Army in Iraq (IAI)	Nationalist	0.26	0.44	0.26	1.03	1.15	0.9
Iraqi Jihadist Leagues (IJL)	Jihadist	-	0.33	0.2	-	1.06	1.27
Islamic Jihad Brigades (ISJIBR)	Jihadist	0.36	0.45	-	1.63	1.72	-
Islamic Front for Iraqi Resistance (JAMI)	Nationalist	0	0.26	0.08	1.33	2	1.94
Just Punishment Brigades (JPB)	Jihadist	-	0.49	0.4	-	1.07	1.16
Mujahidin Army (MA)	Nationalist	0.2	0.3	0.3	1.15	1.54	1.36
Army of Naqshabandi Order (NAQSH)	Nationalist	-	0.3	0.13	-	2	1.94
Rashidin Army (RA)	Nationalist	0.14	0.15	0.08	2	2	1.94
Saad Bin Abi Waqqas Brigades (SBAW)	Jihadist	-	0.45	0.29	-	1.33	1.09
Shield of Islam Brigade (SIB)	Jihadist	-	0.4	0.53	-	1.47	0.99
Victorious Sect Army (VSA)	Jihadist	0.36	0.45	-	1.48	1.06	-

Methodology

Hypothesis 1 (H1) predicts that if militant groups share similar ideologies, then alliances and cooperation are more likely. Hypothesis 2 (H2) predicts that if militant groups share similar identities, then alliances and cooperation are more likely. We evaluate H1 and H2 with three testing strategies. First, we examine network graphs for evidence of sorting effects based on ideology and identity. Second, we test for homophily using ERGMs for leadership alliance and foot-soldier cooperative networks across the three time periods. And third, we provide qualitative evidence illustrating the role of ideology and identity in leadership alliances and foot-soldier cooperation.

(Can you identify and describe the best testing strategies for the first part here? Figure 2 gets at H1 and Fugure 3 gets at H2. Perhaps do the analysis for all 3 time periods and include the most illustrative time period and simply mention how the other 2 periods were in comparison. I restructured this section to allow for joint assessment of H1 and H2, so our analysis isn't repetitive when we interpret the ERGM results in the next section.)

To further evaluate the hypotheses related to militant group ideology and identity we estimate leadership alliances and foot-soldier operational cooperation using an exponential random graph model (ERGM). Tie values indicate the number of interactions between groups while conflict frames and targeting policies are nodal attributes. ERGMs generate a probability distribution of all potential graphs with the same number of nodes via Markov-Chain Monte Carlo. We generate models to assess whether graphs with particular parameters are more likely given this distribution. Models for binary outcomes used in international relations assume that observations of the dependent variable are independent and identically distributed. By contrast, network behavior violates this assumption and dependency between ties is a feature of substantive interest. In addition to describing observed militant networks, we test whether they exhibit evidence of selective processes. Our hypotheses predict that these networks will demonstrate a tendency for assertive mixing, or homophily, based on group-level similarities.

Given that the observed network is only one possible permutation of ties among nodes, the ERGM allows us to test hypotheses relating both the topology of the network and the characteristics of the nodes to the likelihood of observing a given structure. The model implementation uses Markov Chain Monte Carlo maximum likelihood to simulate many networks, conditional on the characteristics of the observed network of Y_{ij} ties between *n* actors. The probability of the observed network is represented by the following function, where θ is vector of parameters, g(y) represents a vector of sufficient statistics, and k(θ) is a normalizing constant.

$$P(Y = y) = \frac{\exp(\theta' g(y))}{k(\theta)}$$

The ERGM coefficients can be interpreted as conditional log odds where a change in a covariate refers to the change in the log odds of observing a tie between y_i and y_j. The conditional log odds of a tie, where Y_{ij} is an actor pair in network Y and $\Delta(g(y))_{ij}$ is the change when Y_{ij} moves from 0/1, are given by:

$$P\left(Y_{ij} = 1\right) = \theta' \Delta\left(g(y)\right)_{ij}$$

A change statistic for the network can be defined as the change to the structure induced by the presence or absence of y_{ij}:

$$\Delta_g(y)_{i,j} = g\left(y + (i,j)\right) - g(y - (i,j))$$

We estimate the homophily effect of ideology and identity on undirected ties between groups to assess if differences in group frames and targeting policy influence the propensity to form leadership alliances or cooperate at the foot-soldier level.

EMPIRICAL FINDINGS

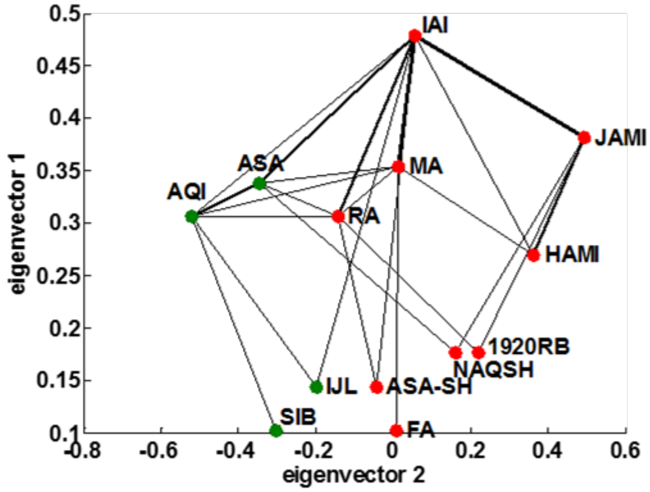
The Iraq War

A U.S.-led coalition invaded Iraq in March 2003, quickly defeating opposition forces and removing Saddam Hussein's Ba'athist government from power. The invasion, and subsequent Iraqi military defeat, led to widespread political, economic, and social instability. Political, ethnic, and sectarian tensions fueled over a decade of violence in Iraq. During this time period a variety of actors formed and dissolved coalitions. Militant factions changed across time as groups cooperated to different degrees at both the leadership and operational foot-soldier levels.

Militant groups operated in a common strategic environment and shared opposition to both foreign forces and the extant national government. The common environmental pressures and loosely aligned goals might lead one to conclude that groups used violence similarly. They primarily combat foreign troops and battle government security forces. However, in Iraq there was significant divergence among militant organizations with respect to the types of attacks and targets they claimed. The Jaish al-Rashideen, (RA) for example, largely defined itself in opposition to the U.S. Coalition presence whereas the Saad bin Abi Waqas Brigades (SBAW) carried out a number of attacks against

Shiite rivals and Sunni co-ethnics. Figure 2 shows the foot soldier operations network in our study during the period from 2007-2009 with groups colored by their nationalist/jihadist identity. The correlation between the first and second eigenvectors of the network matrix indicate a homophily driven structure (corr = .77, $p < .01$).

Figure 2: Insurgent joint cooperation network. Red groups are Nationalist, green are Jihadist. The first and second eigenvectors of the network matrix correspond to the 'global' and 'local' respectively where higher scores indicate a more central position in the network.



These foot-soldiers show greater cooperation across ideological barriers than leaders. Rifts within Iraq's Sunni insurgency influenced the evolution of the conflict and factional rivalry was arguably a cause of the Sunni Awakening and the movement against Al-Qaeda in Iraq. Competition between organizations over experienced fighters and active supporters ran contra to the notion of broad popular support for a monolithic insurgency. The Islamic Army in Iraq, for example, attempted to build a 'big tent' of ideological support, bridging the divide between groups motivated by Iraqi nationalism and those that espoused a more Jihadi rhetoric.

ERGM results

Table 3 shows the results of our exponential random graph models. The edges term is equivalent to the intercept, the baseline propensity to form ties. Because social networks are often low-density compared to the total possible ties, we expect a negative intercept as the overall propensity for ties is low. Targeting policy is operationalized as a difference measure, higher dyadic values indicate that two groups are further apart ideologically.

Table 3

Foot-soldiers - Joint Operations Network

	2003-05	2005-07	2007-09
Edges	-2.833**	-1.590***	-1.079**
	(1.099)	(0.481)	(0.530)
Identity	0.000	1.362***	1.036**
	(0.867)	(0.501)	(0.493)
Targeting policy	2.610**	-0.985*	-1.000*
	(1.133)	(0.555)	(0.595)
AIC	47.873	208.799	166.191

Leadership - Joint Statements Network

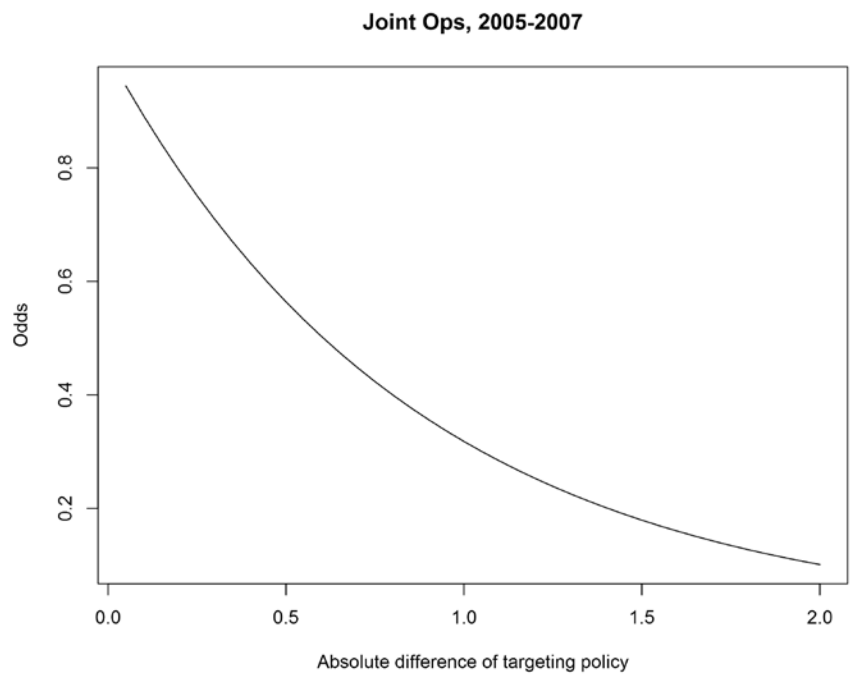
	2003-05	2005-07	2007-09
Edges	-1.059*	-2.343***	-2.163***
	(0.526)	(0.646)	(0.431)
Identity	-0.583	3.249***	2.178***
	(0.831)	(0.765)	(0.551)
Targeting policy	1.222	-1.716**	-1.710***
	(0.876)	(0.719)	(0.640)
AIC	53.824	184.782	151.879
Groups	9	18	16

*p < .1; **p < .05; ***p < .01

The ERGM results provide additional evidence for our hypotheses that ideology and identity contribute to the pattern of cooperation and alliances between militant groups. The positive coefficient on the identity variable indicates that during the 2005-2007 time periods militant groups were more likely to form ties with others when they shared a Nationalist or Jihadist orientation. As seen in Figure 2 this effect is particularly strong during the 2005-2007 period when the Iraqi Jihadist League (IJL) is the sole Jihadist group to have any official leadership ties to Nationalists. The ERGM results indicate that the patterns we observe are not due to chance, group-level identity is contributing to the structure of the network. The maximum possible distance (see Table 1) during 2005-2007 is about 1.44. This is the ideological distance between the Army of Naqshabandi Order (NASQH) and al Qaeda in Iraq (AQI), corresponding a less than 5% probability of a tie. During the same period, the odds of an alliance between two foot-soldier groups increase by 3.9 if they have the same identity. Figure 3 shows the decline in the odds of a tie between foot-soldier groups as the ideological distance grows based on time period 2.

Likewise we see a negative targeting policy effect in the second and third time periods for both networks. Two groups with disparate ideologies, as measured on our targeting index variable, are less

Figure 3: Odds of i-j tie decrease as absolute value on targeting policy grows.



likely to form an alliance than two groups with similar ideologies. For the leadership network, 2005-2007, two groups with the same identity have a 71% probability of allying. For the foot-soldier network the probability is 44%. If those foot-soldiers had a difference of .52 on their ideology variable, equivalent to the difference between the 1920 Revolutionary Brigades and the Islamic Army in Iraq, the probability of an alliance decreases to about 32%. Of course we note that this is a probabilistic econometric model. Considering the distribution of ties in the two networks shown in Figure 2 we observe that the SBAW, with a middling targeting policy value (1.33) claimed no ties at all with other groups. Moreover, the IAI (targeting policy 1.15) had a number of foot-soldier level ties to groups with higher scores as well as several Jihadist groups. While leadership appears to demonstrate a stronger tendency toward organizing based on identity, there groups that form ties across identities. Ideology alone is insufficient to explain the observed patterns as targeting policies vary within the identities and within groups over time. The econometric results presented here show that these alliance networks are unlikely to have arisen by chance.

The model estimates for the first time period are reflective of the smaller number of groups during the initial phase of the insurgency and the high connectedness relative to the other periods. Among leadership there appears to be no significant pattern of alliances based on ideology and identity from 2003-2005. The non-significant coefficients on the identity homophily term during the same period could indicate that the orientation of the various factions had not yet coalesced firmly around Nationalist/Jihadist goals. It may also mean that the various sides were more strongly oriented around other, unobserved values and that our identity categories became increasingly salient as the insurgency went on.

The Ansar al-Sunnah group, for example, refused to work with Zarqawi despite nearly identical goals and prior cooperation with Al-Qaeda. (Zech and Kelly 2015).

CONCLUSION

This paper argues that militant group ideology and identity helps to explain leadership allianecs ande joint operations among foot-soldiers. We present a novel approach to understanding the dynamic factional behavior of a multi-group insurgency that lacks two clear ideological poles posited in most models of insurgent-government competition. We employ data gathered from groups' actual statements to estimate their cooperative networks and policy positions. Social network tools help us to identify and analyze the evolution of endogenous social structures using exogenous characteristics militant groups. Using an exponential random graph model to accommodate the non-independence of observed cooperative ties we find evidence that militant ideology and identity, measured through conflict frames and targeting policies, help explain militant cooperation among both leadership and foot-soldiers during the Iraq War. A purely power-based argument that treats ideology and identity as incidental would predict, for example, that cooperation with AQI, the most well-known international Jihadist group, was equally likely for any of the groups in our sample. In contrast we find that ideology, measured by a straightforward Jihadist/Nationalist dichotomy, and preferences about legitimate targets of violent insurgent actions, have a significant role in the factional alignment. These results also speak to the utility of big-data methods for text analysis in security studies. Insurgent and terrorist groups increasingly broadcast their beliefs and actions through websites and social media. These statements are not just 'cheap talk' and can serve as a valuable source of data for identifying ideological orientations and identities. Groups that have publicly claimed allegiance to the Islamic State—for example, Boko Haram and elements of the Pakistani Taliban—do so for strategic reasons. These results also motivate additional considerations regarding group identity. Hybrid groups, for example with a mixed jihadist-nationalist identity, are likely to emerge organically within an insurgency. Such groups are often in a structural position to enjoy rapid growth as they bridge the gap between opposing camps and appeal to a large range of fighters. Hybrid groups may therefore seek a more maximal political outcome relative to 'pure' jihadist or nationalist factions; embracing, for example, both Shariah rule and consolidated central power. Future research would do well to explore the emergence, substantive composition, and survival of hybrid groups as well as their roles in bridging the structural gap between opposed camps. These dynamics are likely to play a significant role in the ongoing Syrian civil war, as well as future conflicts.

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14. ABSTRACT

This report describes research conducted under the subject grant by the Applied Physics Laboratory of the University of Washington. Key results of this research effort include: (1) the development of a prototype software package for leadership network modeling and analysis which integrates quantitative techniques from nonlinear systems theory and network science; (2) the development and application of methods of relating network structure and ideology for insurgent movements; and (3) the development of a mathematical model for the simultaneous evolution of insurgent alliance ties and their allocation of force policies.

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