

# Self-Consistent and Manipulative Behavior in Social Choice as a Repeated Nash Game on a Graph

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42nd annual meeting of the AMASES, Naples, 13-15 September 2018

# Overview

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- A social choice procedure as a repeated Nash game between the social agents
- Stability analysis of the derived strategies
- Topology design, which aims to the stabilization of these strategies

- Develop a model for social choice procedures, which captures the conformity and manipulative behaviors
- A similar model has been proposed by R.Etesami et al.('17).
- We have introduced dynamically changing internal beliefs.
- Develop a graph topology design methodology in order to influence the effects of manipulative behaviors.
- Applicability of the design methodology to many problems in other areas of interest.

- Each agent has an internal belief or opinion ( $\theta_i(k)$ ) and an expressed opinion or action ( $u_i(k)$ ) at each time step  $k$
- The opinion shaping criteria model conformity, parameterised by  $c_i$ .
- The action shaping criteria model manipulative behaviors, parameterised by  $g_i$ .

- Let  $A$  be the adjacency matrix of the communication graph.
- $d_i$  is the degree of node  $i$  and  $D = \text{diag}\{d_i\}$  is the degree matrix.
- $C = \text{diag}\{c_i\}$  is a diagonal matrix containing the parameters  $c_i$ .
- $G = \text{diag}\{g_i\}$  is also a diagonal matrix containing the parameters  $g_i$ .
- $N_i$  denotes the neighborhood of agent  $i$ , ie  $N_i = \{j : (i, j) \in E\}$ , where  $E$  is the set of edges.
- Let  $\mathbf{1}$  stands for a vector with all its coordinates equal to 1 and  $\mathbf{I}$  for the identity matrix, of proper dimension

# Opinion Dynamics

At each step of the procedure, the opinion of each agent is formed so as to minimize the following criterion:

$$J_{o_i}(k+1) = c_i(\theta_i(k+1) - \theta_i(k))^2 + d_i(\theta_i(k+1) - \frac{\sum_{j \in N_i} \theta_j(k)}{d_i})^2 \quad (1)$$

Thus, these dynamics arise:

$$\theta_i(k+1) = \frac{c_i}{d_i + c_i} \theta_i(k) + \frac{1}{d_i + c_i} \sum_{j \in N_i} \theta_j(k) \quad (2)$$

Equivalently, with matrix notation:

$$\theta(k+1) = (D + C)^{-1}(A + C)\theta(k) \quad (3)$$

which are known to converge to a limit vector  $\theta^c$  under two non restrictive assumptions, as shown for example by M.DeGroot ('74) or by A.Olshevsky and J.Tsitsiklis ('09).

# Action Dynamics

At each step of the procedure each agent knows only the previous actions of her neighbors, so her estimation of the social outcome is:

$$\tilde{u}_i(k) = \frac{\sum_{j \in N_i} u_j(k-1) + u_i(k)}{d_i + 1} \quad (4)$$

Thus, her action shaping criterion has the following form:

$$J_{a_i}(k) = (u_i(k) - \phi(\theta_i(k)))^2 + g_i(\tilde{u}_i(k) - \phi(\theta_i(k)))^2 \quad (5)$$

and the action dynamics which derive from its minimization are:

$$u_i(k+1) = \left(1 + \frac{d_i g_i}{g_i + (d_i + 1)^2}\right) \phi(\theta_i(k+1)) - \frac{g_i}{g_i + (d_i + 1)^2} \sum_{j \in N_i} u_j(k) \quad (6)$$

or with matrix notation:

$$u(k+1) = G_\theta \Phi(\theta(k+1)) - G_u A u(k) \quad (7)$$



In the last equation (7):

$$G_\theta = \text{diag}\left\{1 + \frac{d_i g_i}{g_i + (d_i + 1)^2}\right\} \quad (8)$$

$$G_u = \text{diag}\left\{\frac{g_i}{g_i + (d_i + 1)^2}\right\} \quad (9)$$

Let  $z(k) = [\theta_1(k) \dots \theta_N(k), u_1(k) \dots u_N(k)]^T$   
and the resulting augmented system describing its dynamics:

$$z(k+1) = \begin{bmatrix} (D+C)^{-1}(A+C) & 0 \\ G_\theta \Phi \circ (D+C)^{-1}(A+C) & -G_u A \end{bmatrix} z(k) \quad (10)$$

## Lemma

*If the matrix  $A_u = G_u A$  is asymptotically stable, ie  $|\lambda_i(A_u)| < 1, \forall i$  and the function  $\Phi$  is continuous in  $\mathcal{R}^n$  and locally Lipschitz in a neighborhood of  $\theta^c$  with a Lipschitz constant  $L_\Phi$ , then the coupled dynamics (10) will be stable.*

# Sufficient Condition

Since the matrix  $(D + \mathcal{I})^{-1}A$  is a substochastic matrix and thus a stable one, a simple but restrictive sufficient condition for the stability of the whole system is the spectral radius

$\rho(G_u(D + \mathcal{I})) = \max\{\|\lambda_i(G_u(D + \mathcal{I}))\|, i = 1 \dots N\}$  to be less than one as well or equivalently

$$\frac{(d_i + 1)g_i}{g_i + (d_i + 1)^2} < 1 \Rightarrow g_i < d_i + 2, \forall i \quad (11)$$

Thus, a useful remark for the topology design initialisation can be stated here. If we consider a graph topology with:

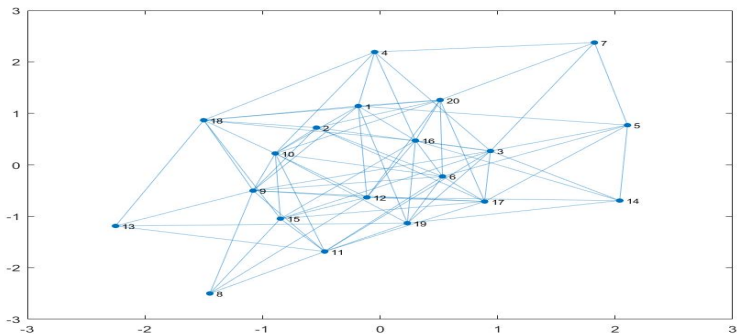
$$d_i > g_i - 2, \forall i \quad (12)$$

then the dynamics are stable on this topology.

# Simulation parameters

- We consider a group of 20 social agents, which communicate with each other over several different graph structures.
- Their manipulation parameters  $g_i$  and their conformity parameters  $c_i$  remain the same in all simulations.
- Their initial opinions are randomly chosen from the  $[0, 10]$  interval.
- Their initial actions  $u_i(0) = \phi(\theta_i(0))$ , where  $\phi(\theta) = 10 \tanh(\frac{\theta}{10})$ .

# A random graph



**Figure:** A random graph, as introduced by P.Erdős and A.Rényi (1959), with edge probability  $p = 0.4$ .

1

<sup>1</sup>This random graph has  $|E| = 114$  edges.

# Stable example

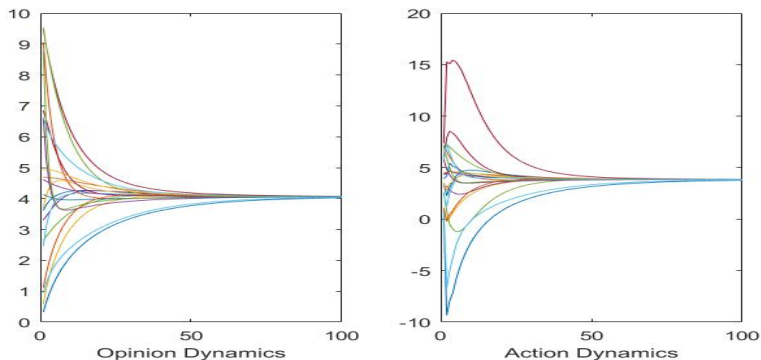


Figure: Opinion and action dynamics on a random graph with edge probability  $p = 0.4$ .

# Unstable example

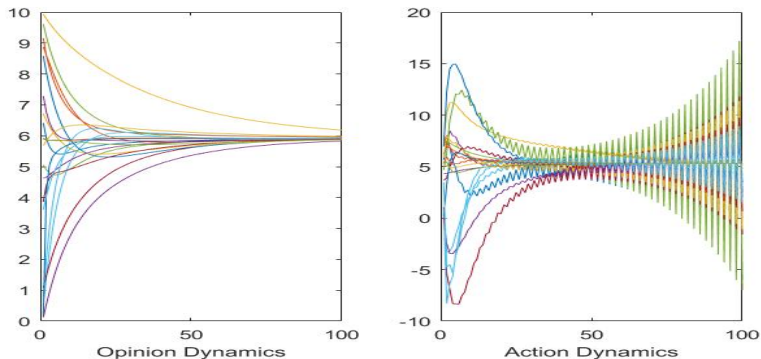


Figure: Opinion and unstable action dynamics on a random graph with edge probability  $p = 0.3$ .

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<sup>2</sup>The random graph considered in this simulation has  $|E| = 52$  edges.

# Stabilization ideas

Considering the problem of choosing a proper graph structure, which would result in stable dynamics, and be as close as possible (here with respect to the edge number  $|E|$ ) to the aforementioned unstable one, we make several experiments beginning from an  $L^*$ -lattice which satisfies our sufficient condition ( $L^* > g_{max} - 2$ ),  $L^* = 14$  in this example, and relaxing it as shown in the following table:

<b>Graph structure</b>	$\lambda_{max}(A_u)$	$ E $
$L^*$ -lattice	0.4042	140
8-lattice	0.7758	80
6-lattice	1.0114	60
Small-world	0.9491	60

Table: Stability of several graph structures



# The 8-lattice

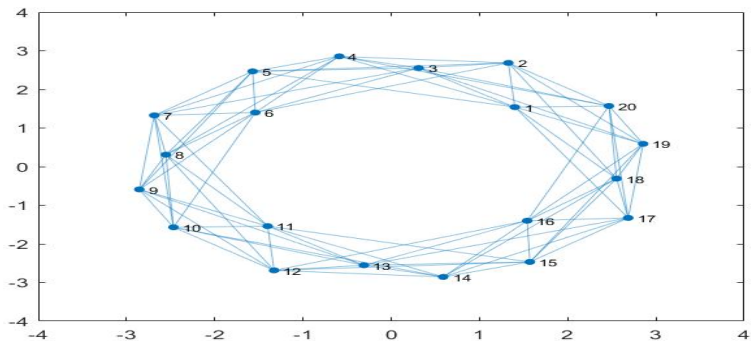
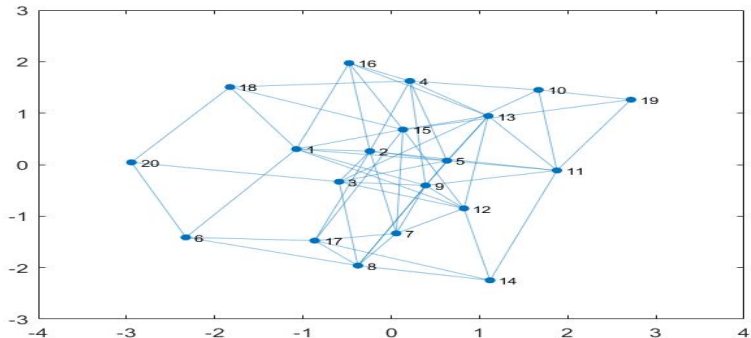


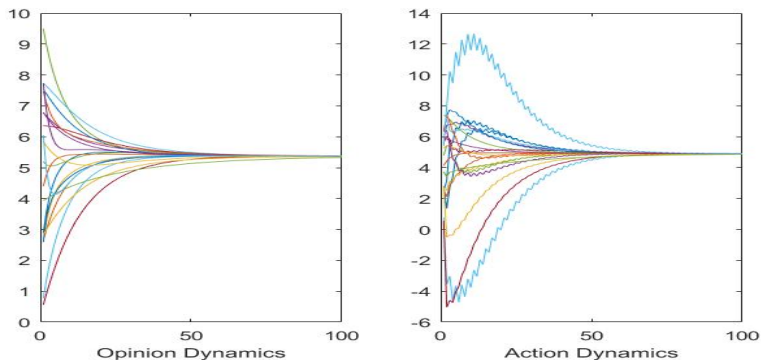
Figure: A lattice graph of node degree 8 .

# The small-world graph



**Figure:** A small-world graph, as introduced by J. Watts and S. Strogatz (1998), derived from a 6-lattice with rewiring probability  $p_r = 0.5$ .

# Stable dynamics on a small-world graph



**Figure:** Opinion and action dynamics on a small world graph resulting from a 6-lattice.

# Topology design problem statement

- Let  $A_0$  be the adjacency matrix of the initial topology.
- Let  $\{P^k, k = 1 \dots \frac{n(n-1)}{2}\}$  be a basis for the symmetric matrices of size  $n$ , with zero diagonal elements. Each  $P^k$  stands for the representation of the  $k$ -th edge at the adjacency matrix of the graph, for a proper enumeration of all the possible edges.
- Let the vector  $x_0$  be the coordinates of  $A_0$  with respect to this basis.
- Let also  $x \in \{0, 1\}^{\frac{n(n-1)}{2}}$  be the vector of changes. If  $x(k)=1$  a change occurs at position  $k$ , else no change occurs at this position.
- Let finally the sign function  $S_{x_0}(k) = 1$  if  $x_0(k) = 0$  and  $S_{x_0}(k) = -1$  if  $x_0(k) = 1$ . This function indicates if the possible change corresponds to the addition of a new edge or to the removal of an existing one.

So the adjacency matrix of the designed topology has the following form:

$$A(x) = A_0 + \sum_{k=1}^{n(n-1)/2} x(k)P^k S_{x_0}(k) \quad (13)$$

# Topology design problem statement (cont'd)

The degree matrix changes accordingly:

$$D(x) = \sum_{i=1}^n e_i (A(x)\mathbf{1})^T P_d^i \quad (14)$$

Subsequently, we define the matrix function, in accordance with the equation (9):

$$G_u(x) = G(G + (D(x) + I)^2)^{-1} \quad (15)$$

and consequently

$$A_u(x) = G_u(x)A(x) \quad (16)$$

which are nonlinear with respect to the decision variables  $x$ .

The criterion for choosing a design is the minimum change from the initial graph structure. Thus, we have to minimize  $\|x\|_1$ , which is equivalent to the minimization of the linear objective  $\mathbf{1}^T x$ .

# Topology design problem statement (cont'd)

The resulting problem is:

$$\underset{x,P}{\text{minimize}} \{ \mathbf{1}^T x \} \quad (17)$$

$$x \in \{0, 1\}^{n(n-1)/2} \quad (18)$$

$$P > 0 \quad (19)$$

$$A(x)G_u(x)PG_u(x)A(x) - P < 0 \quad (20)$$

The last two constraints can be relaxed as follows in order for the feasible region to become closed:

$$P \geq \epsilon \mathbf{1} \quad (21)$$

$$A(x)G_u(x)PG_u(x)A(x) - P \leq -\delta \mathbf{1} \quad (22)$$

The parameters  $\epsilon$  and  $\delta$  must be carefully chosen to be very small so as to not reject many feasible solutions.

In this problem formulation several linear constraints may be added without changing its difficulty.

# Characteristics of the design problem

The last constraint  $A(x)G_u(x)PG_u(x)A(x) - P \leq -\delta \mathbf{I}$  is nonlinear in the decision variables  $x$ . So, we consider the change of variables  $Z = G_u(x)PG_u(x)$  (it holds that if  $P > 0$  then  $Z > 0$  and vice versa):

$$A(x)ZA(x) - G_u^{-1}(x)ZG_u^{-1}(x) \leq -\delta \mathbf{I} \quad (23)$$

This last constraint (23) is polynomial in the decision variables  $x$  and with a proper change of variables it can be converted to a Bilinear Matrix Inequality (BMI).

The feasibility of a BMI is known to be a nonconvex problem in the general case [M.Mesbahi, M.G.Safonov,G.P.Papavassilopoulos(2000)]  
So the same holds for our initial problem (17)-(20).

Our research direction now is to develop a proper algorithm to deal with the BMI constrained integer programming problem for the network topology design. Specifically, some kind of organised random search algorithm will be considered, such as:

- Genetic algorithms
- Particle swarm optimization
- Simulated annealing



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# The End