Modeling and Simulation of Social Systems

An overview

Workshop on Mechanism Design and Computational Modeling of Social Systems

Rasoul Ramezanian

Sharif University of Technology

Department of Mathematical Sciences, group of computer sciences

Artificial Societies



2

Generative Social Science

- Generative Science is an interdisciplinary and multidisciplinary science that aims to <u>discover</u> how simple and local microbehaviors emerge complex macro- behavior.
- For example, we may ask
- 1. Which simple and local behaviors of individuals have generated Persian language as an emergent process?
- 2. Which simple and local behaviors of individuals have generated graph of facebook which has small world property?
- 3. How our brain works as a complex system?
- 4. etc

Generative Social Science

Generative sciences include: psychology, cognitive science, computational social science, evolutionary biology and etc.

Generative Social Science

- Generative social science provides a new method for reasoning besides famous methods inductive and deductive reasoning.
- To show that some micro behaviors B cause to <u>emerge</u> some macro structure A of the social system reason in the following way:

<u>1- simulate</u> the society by constructing an <u>artificial society</u> where all agents are set to <u>act according</u> B to and then

2- run the society to see if macro structure A arise.

- An artificial society consists of a set of individuals who
- 1- locally interact
- 2- have local information
- 3- are bounded rational
- 4- are heterogeneous
- 5- make decision in a decentralized manner (autonomy)

The artificial society (as a computer program) is run and the aggregation of individuals' attributes are considered as macro-structure of the system.

- Local interaction: agents interact with neighbors (neighbors could be space neighbors, family, friends, and all people who are accessible)
- Local information: Each agent has a local vision (furthest possible distance that the agent can access).
- **Bounded rationality**: Agents have neither global information nor infinite computational capacity. They use simple rules based on their local information.

- Heterogeneous: Representative agent methods—common in dynamical system model—are not used in generative social sciences.
- Agents are not aggregated into a few homogeneous pools.

Every individual is explicitly represented and individuals may differ from one another in lots of ways: by wealth, preferences, memories, decision rules, social network, locations, genetics, culture, and etc.

 Autonomy: There is no central, or "top down," control over individual behavior. Of course, there will generally be feedback between macrostructures and microstructures but as a matter of model specification, no central controllers is assumed.

Some Artificial Societies

• Gen Pool: Swimbots

1- locally interact (interaction with <u>food</u> and with other <u>swimbots according to their sexual preferences</u>)

2- have local information (each swimbot has a bounded vision to find foods and partner for reproduction)

3- are bounded rational (they decide according to some simple rules)

4- are heterogeneous (they have <u>different sexual preferences</u> and <u>ability to move</u>)

5- are autonomous (there exists no central over swimbots)

- An Artificial society for modeling the rebellion of a subjugated population against a central authority
- 1. Each agent has an individual level of complaint toward the central authority.
- 2. Complaint is based on the agent's PERCEIVED-HARDSHIP, which is assigned randomly at startup, and on GOVERNMENT-LEGITIMACY
- Each agent calculates an individual risk of rebelling at the beginning of each turn. This ESTIMATED-ARREST-PROBABILITY, is based on the number of cops and already rebelling agents within his local VISION.



Moving from Macro Level Simulation to Artificial Society Simulation

Modeling



- System dynamics has its roots in systems of difference and differential equations.
- A real system, with its properties and dynamics, is modeled using a system of equations which derive the <u>future state</u> of the system from its <u>current state</u>.
- System dynamics is restricted to the <u>macro level</u> in that it models a part of reality.
- Systems dynamic does <u>not model</u> agents, it models population (stocks), the rate (flow) of changes of population, and the <u>feedback</u> of stack and flow on each other.



- A differential equation model of doves, hawks and lawabiders
- We want to model a **society** whose agents are continually competing with each other to obtain a resource.
- Every resource belongs to someone, thus conflicts arise between resource owners and those who want an additional resource.
- Each agent of the society has one the following three strategies: hawk, the dove and the law-abiding strategies.

- The **dove** never tries to get hold of others' possessions, but waits until they are given up, and himself abandons his resource as soon as he is attacked. If two compete for the same resource, one of them gets it with equal probability.
- The hawk always tries to get hold of others' resources by means of aggression and gives up only if he receives serious injuries.
- The law-abider never tries to get hold of others' possessions, but waits until they are given up, and he defends his possession by counterattack until he either succeeds or is defeated

• We let

- 1. u be the utility of having the resource
- *2.* c_D be the cost of waiting
- *3.* c_H be the cost of fighting
- 4. $c_D < u < c_H$

	Dove	Hawk	Law-abider		
Dove	$\frac{u}{2} - c_D, \frac{u}{2} - c_D$	0, u	$\frac{0+\frac{u}{2}-c_D}{2}, \frac{u+\frac{u}{2}-c_D}{2}$		
Hawk	u, 0	$\frac{u-c_H}{2}, \frac{u-c_H}{2}$	$\frac{\frac{u-c_H}{2}+u}{2}, \frac{\frac{u-c_H}{2}+0}{2}$		
Law-abider	$\frac{u+\frac{u}{2}-c_D}{2}, \frac{0+\frac{u}{2}-c_D}{2}$	$\frac{\frac{u-c_H}{2}+0}{2}, \frac{\frac{u-c_H}{2}+u}{2}$	$\frac{u}{2}, \frac{u}{2}$		

• For
$$c_D = 3$$
, $c_H = 20$, $u = 10$, we have

	Dove	Hawk	Law-abider
Dove	2, 2	0, 10	1,6
Hawk	10, 0	-5, -5	2.5, -2.5
Law-abider	6, 1	-2.5, 2.5	5, 5

- Let r_{ij} be the value in the table where $i, j \in \{H, D, L\}$.
- Let p_i(t) be the proportion of population for type i
 ∈ {H, D, L} at time t.
- The average gain of type i at time t is $y_i(t) = \sum_j r_{ij} p_j(t)$
- The average gain of all types at time t is $y(t) = \sum_{i} y_{i}(t)p_{i}(t)$
- We let

- We let $F_i(t) = y_i(t) y(t)$ be the difference between the average gain of type i and the average gain of society.
- The following equation model the society of Hawk-Dove-Lawabiders

 $p_i(t+1) = p_i(t)[1 + F_i(t)]$

- In this systems dynamic model, the dynamic of proportion of each type is discovered thought time.
- In this modeling, agents in the society are not modeled. We do not have an artificial society of bounded rational agents who locally interact.
- The model is restricted to the relation between macro-level attributes. The model cannot help us to discover that which micro-level behaviors cause the dynamic of proportions.

• System dynamic diagram of Hawk-Dove-Law



• Initial Proportion: 90% Hawk, 5% Dove, 5% Law



- In systems dynamic a society is modeled as a variable not a set of individuals (agents).
- Systems dynamic models a society as an indivisible wholes and does not consider that actually a society consists of lots of individual persons.
- For example, the tax of the society depends on the tax that each individual person pays. If governments wants to change the <u>tax formula</u> then it effects the income of each person in different way. Systems dynamic cannot explain these cases.
- The Micro-level transition overcome this problem by going to the individual level.

- In Micro-level simulation, the society modeled by
- A <u>data base</u> DB of agents' attributes profile for example: agent1=[alive, age, sex, martial status, education, income, employment, ...]
- 2. A number of <u>stochastic transitions</u> such as <u>aging</u>, <u>death</u>, <u>divorce</u>, <u>marriage</u>, <u>employment change</u> <u>related to changing</u> <u>each attribute</u>.

Each stochastic transition is function form **DB** to [0,1]. For example, **death(agent1)=0.3** means that at the next step agent1 is dead with probability 0.3, and alive=0.

To move from step t to step t+1, all stochastic transitions are applied on DB and DB is **updated**.



- To discover the dynamic of macro-level attributes of the society through time, we <u>aggregate</u> individual attributes.
- For example, if we want to know the dynamic proportion of married people at each time step t, we aggregate the number of agents whose marital status is married. Note that the martial status changes by two stochastic transitions Divorce and Marriage.
- In this way macro-level attributes of the society are caused by the aggregation of micro-level attributes of agents.
- Is it an Artificial Society? The answer is NO. Although, we have a pool of agents but their fate is independent of each other! Agents do not interact with each other, and do not learn.

- Let T be a stochastic transition. For each agent $I_j = [a_{j1}, a_{j2}, ..., a_{jn}]$ (where a_{jk} is the kth attribute of agent I_j). $T(I_j) \in [0,1]$ is computed just according to $a_{j1}, a_{j2}, ..., a_{jn}$.
- In this way, the next status of an agent does not depend on what the society he lives in.
- To overcome this problem, we discuss Multi-level Simulation.

- We are faced with a society with its macro attributes (such as the size of population, birth rate, death rate, gender distribution, divorce rate, marriage rate, and etc.)
- The society consists of a possibly great number of individuals with their own attributes (such as sex, age, marital status, employment status, annual income, and etc.)
- Social macro-attributes depend on aggregated individual attributes.
- Individual attributes in turn depend on the social attributes as well.

- For example, the chance that individual divorces this year in Iran can be estimated via the divorce rate in IRAN. Or the chance that an individual dies this year in Iran can be estimated via the death rate in in IRAN.
- In this way, we have a cyclic dependence in multi level simulation.
- Multi level simulation is similar to stochastic micro level simulation except that the outcome of stochastic transitions do not just depend on agent's attribute it also depend on social attributes.

- A stochastic transition T_i is function from both agent's attributes and social attributes.
- Let [a_{j1}, a_{j2}, ... a_{jn}] be the profile attributes of agent j and [s₁, s₂, ..., s_m] be the profile attributes of society at step t-1.
- At time step t, social macro attributes (such as the size of population, birth rate, death rate, gender distribution, divorce rate, marriage rate, and etc.) updated by <u>aggregating</u> <u>individuals' attributes</u> who lives in the society.
- Then the status of attribute a_{ij} of agent j will change with probability $T_i([a_{j1}, a_{j2}, ..., a_{jn}], [s_1, s_2, ..., s_m])$.

- Consider a society whose decision on a certain issue may be either 'yes' or 'no'.
- At the beginning, we have 50 per cent `yes'.
- Depending on how strongly individuals' opinions are coupled
 (κ) to the majority, after a while some individuals change their
 opinion from <u>yes to no</u> or from <u>no to yes</u>.
- We can describe the opinion formation model mathematically as a stochastic process based on the individual transition probabilities from 'yes' to 'no' and vice versa.

$$\mu_{yes \leftarrow no} = \nu \exp(\pi + \kappa x)$$

$$\mu_{no \leftarrow yes} = \nu \exp\left[-(\pi + \kappa x)\right]$$

$$x = \frac{n_{yes} - n_{no}}{n_{yes} + n_{no}}$$

- v is a flexibility parameter; the higher it is, the higher will be both transition probabilities, and the more often opinion <u>change happen</u>.
- π is a preference parameter; the higher it is, <u>the higher will be</u> <u>the probability of changing to 'yes'</u>, and the lower will be the probability of changing to 'no'.
- κ is a coupling (to majority) parameter; if it is high, then the influence of a 'yes' majority on an individual change to 'yes' is high (and the same is true for the influence of a 'no' majority on an individual change to 'no'.
- NOTE THAT STOCASTIC TRANSITIONS DO NOT JUST DEPEND ON INDIVIDUAL ATTRIBUTE TEHY ALSO DEPEND ON *x* WHICH IS GOLBAL VARIABLE.

 We can also model Hawk-Dove- Law abiders via this approach by determining:

 $\mu_{D\leftarrow H},\,\mu_{D\leftarrow L},\,\mu_{H\leftarrow L},\,\mu_{H\leftarrow D},\,\mu_{L\leftarrow D},\,\mu_{L\leftarrow H},$

Is it an Artificial Society?

The answer is NO. Although, we have a pool of agents that **their fate** is dependent to each other! Agents **do not interact** with each other, and **do not learn**.

- In multi level modeling, agents interact globally with the whole of society, in this modeling, it is not possible to model local interactions between an agent and its neighbors.
- To overcome the problem of local interaction, we go to cellular automata.



- Game of Life:
- 1. We have a grid of cells.
- 2. Each cell at each time step is alive or dead

				 1 1
				1 1 11 1
				8 8 8
				1 1 8

- 1. A living cell remains alive if it has two or three living neighbors, otherwise it dies.
- 2. A dead cell remains dead unless it has three living neighbors, and it then becomes alive



- A cellular automata generally consists of following parts:
- 1. A set **C** of identical **cells** (often several thousand even millions) arranged in a graph. Each cell is a node of the graph and it neighbors are those cell which are linked to them.
- 2. A finite set **S** of status for cells. Each cell can be in one of the status in **S** for example, 'on' or 'off', or 'alive' or 'dead'.
- 3. Time advances through the simulation in steps. At each time step, the status of each cell may change.
- 4. The status of a cell after any time step is determined by a rule which specify how that status depends on the previous status of that cell and the status of the cell's immediate neighbors.

 Suppose that m be an upper bound for the degree of the underlying graph. Then a rule for cellular automata is a function

$$f:\underbrace{S \times S \times S \times \cdots \times S}_{m+1} \to S$$

which determines the status of a cell based on its pervious status and the status of its neighbors in the pervious step.

In cellular automata, we have the property of local interaction.

Majority Model

- people adopt a fashion only if the majority of their friends have already adopted it.
- We have two fashions white and black.
- Our simple model has just a **single rule**:

1. The new cell state is the state of the majority of the cell's neighbors, or the cell's previous state if the neighbors are equally divided between white and black.

Majority Model



Majority Model



Dove Hawk Law-Abider Model

- Agents wander from patch to patch in a somewhat random fashion
- Each move costs energy, but they can get energy from patches.
- If they arrive alone, then they get all the energy but if there is another agent, then they get a payoff depending on the type of the agent who is there with.
- If the energy of an agent reaches a certain level, it reproduces asexually, and if its energy reaches zero, it dies.
- Patches require a certain amount of time before they recover their resource value. Patches with resources available are green; they are a lighter color if their resources are not available.

Dove Hawk Law-Abider Model

