Synchronization and Emergence of Intelligence in Networked Agents

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AIM and Research Questions (1)

- Crowds are often **foolish**, but crowds are **wise** under certain conditions.

  - Under what mechanism can we improve the performances of the complex systems that involve human decision-makings?
AIM and Research Questions (2)

Networked Society: All connected with which we interact

Positive and negative network effects

• Positive networks effects are obvious
  : More people means more benefits
  (Wikipedia depends on positive network effects)

• Negative network effects result from resource limits
  : More persons begin to decrease the value of a network
  (daily-life traffic congestions, network overloads)
Social atom:
Not observe individual behavior
observe patterns

High

Socio physics
(Complex networks)

Complex adaptive
systems

Multi-agent
systems

Game theory

Collective systems?

Low

Self-interest seeking
Adaptability

Low

High

Scale
Outline

• Emergence by nature vs. Emergence by design
• Madness of crowds vs. Wisdom of crowds
• Types of social interactions
  : Coordination problems
  : Dispersion problems
  : Mixed problems
• Synchronization in complex networks
• Emergent intelligence in networked agents
Emergence by Nature

- Emergence by nature (empirical view)

View emergence as an “innate property” of natural systems

“Systems self-organize into a complex state, poised between predictable cyclic behavior and unpredictable chaos”

Inspires research to discover and explain emergent behaviors
Emergence by Design

- Emergence by design strategies (operational view)
  “System-wide behavior emerges from interactions among individual elements”
  - Some researchers view emergence as a property that is “designed” into systems
  - Inspire research into control techniques to induce desired emergent behaviors
Emergence by Design (2): Illusion of Control?

- **Self-similarities**: Internet throughput
- **Phase transitions**: Synchronization among routers
- **Meta-stabilities**: Distribution of call types in wireless cells

Difficult to predict and control because of phase-transitional behavior

High load → congestion collapse
Madness of Crowds vs. Wisdom of Crowds (1)

• **Social sciences** <crowd psychology: negative sides of human behavior> herding, cascade, group think,…

• **Game theory:** <the problem of a coordination failure>

  The existence of externalities lead to coordination failure

• **Computer science:** <the price of anarchy>

  Selfish behavior may not achieve efficiency at the collective level.
A large collection of people are smarter than an elite few.

He suggests new insights regarding how our social activities should be organized.

: The wisdom of crowds emerges only under the right conditions (diversity, independence, etc)
Diversity of Social Interactions

Type 1: Coordination problems
Agents are better off if they take the same action.
- Consensus problem (control theory)
- Synchronization (physics/complex networks)
- Herding (economics/psychology)
- Gossip algorithm (computer science)
- Coordination game (game theory)

Type 2: Dispersion problems
Agents are better off if they take the distinct actions.
- Congestion problem (control theory)
- Stock markets (economics)
- Minority games (econophysics)

Type 3: Mixture of coordination and dispersion problems
Consensus Problems

♦ “Consensus” means to reach an agreement regarding a certain quantity of interest that depends on the state of all nodes (subsystems).

♦ More specific, a consensus algorithm is a rule that results in the convergence of the states of all network nodes to a common value.

\[ x_i = x_j = \ldots = x_{\text{consensus}} \]
Synchronization: Prevalent appearance in physics and biology

Homogeneity is important for better synchronization
**Synchronization in Globally Connected Networks**

**Observation:**

No matter how large the network is, a globally coupled network will synchronize if its coupling strength is sufficiently strong.

**Good** – if synchronization is useful

---

G. Ron Chen (2006)
Observation:
No matter how strong the coupling strength is, a locally coupled network will not synchronize if its size is sufficiently large.

Good - if synchronization is harmful
Synchronization in Small-World Networks

Start from a nearest neighbor coupled network

Add a link, with probability $p$, between a pair of nodes

Good news: A small-world network is easy to synchronize!

Synchronization and Network Topology

Connectivity of networks does matter for synchronization

\[ \lambda_2 = 0.238 \]

\[ \lambda_2 = 0.925 \]

- \( \lambda_1 = 0 \) is always an eigenvalue of a Laplacian matrix
- \( \lambda_2 \) is called the algebraic connectivity, and is a good measure of synchronization.

\[
\begin{bmatrix}
    k_1 & \{0,-1\} \\
    k_2 & \ddots \\
    \{0,-1\} & \ddots & k_n
\end{bmatrix}
\]

- Laplacian matrix = Degree – Adjacency matrix

Network A

Network B
Agent vs. Social Atom

Mental model

preference, stress
habit, adaptation

Social network changes an agent’s behaviour

External influence

norm, culture
laws, order

D. Green (2006)
Repeated Games on Networked Agents

- Types of pair-wise interactions
  - Prisoner’s dilemma game
  - Coordination game
  - Hawk-dove game
  - Chicken game (battle-of-sexes game)

Local model

Small-world model

Random model

N=50

18 - Complex System '07 (Gold Coast)
Measurement: The Price of Anarchy

- Equilibria of selfish agents are not efficient outcomes (Social optimal is usually not achieved by Nash equilibrium strategy)

**Price of anarchy (POA):**
- Quantify inefficiency in terms of a global objective

\[
\text{Price of Anarchy} = \frac{\text{optimal objective function value}}{\text{objective function value at Nash equilibrium}}
\]

*Collective intelligence do matter to decrease POA*
Fixed Rule vs. Rule Evolution

- **Learning**: Memory-based strategy choice: Memory → $A_t$ (strategy at time $t$)
- **Is a short memory enough or a longer memory may be necessary in more complex games?**
  - Reactionary strategy with history one: $(h_{t-1}) → A_t$
  - Finite history of $k$: \{(h_{t-k}, \ldots, h_{t-2}, h_{t-1})\} → A_t

- **Agents play the game repeatedly by evolving a rule rather than by a fixed rule such as TFT.**

<table>
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<tr>
<th>bit</th>
<th>past strategy</th>
<th>strategy at t</th>
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<tbody>
<tr>
<td></td>
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</table>
# Simulation Results (1)

1. **Dilemma game**
   - Payoff matrix:
     - **C**: 3, 0
     - **D**: 0, 1
   - POA = 3

2. **Coordination game**
   - Payoff matrix:
     - **C**: 1, 0
     - **D**: -9, 0
   - POA = Infinity

3. **Hawk-Dove game**
   - Payoff matrix:
     - **C**: 5, 0
     - **D**: 0, 10
   - POA = 5

![Graphs showing average payoff per generation for different models and payoff outcomes.](image)

- **Lattice model**
- **SW model**
- **RD model**

*The average payoff per generation*
Synchronization in Games on Networks

- What is the impact of the interaction structure on synchronization in games on networks?

- The lattice networks, where the connectivity among agents is mostly reserved, foster to promote to better synchronization

Local model
Small-world model
Random model
Social Interaction: Type 2

- **Type 2: Dispersion problems:**
  Agents are better off if they take the distinct actions.
  - Stock markets
  - Minority games (game theory)
The El Farol Bar Problem/ The Minority Games

Agents gain if they are in the minority side.
Global Minority Games

Minority game: important for the study of fluctuation. Moderate diversity: important for emergence of coordination

\[ \sigma = \sqrt{\langle A - N/2 \rangle^2} \]

A = \# of agents who attended

Efficient coordination is emergent

Challet, Zang (2005)

Nash equilibrium
(S1: 0.5, S2: 0.5)

Number of behavioral rules

random behavior

homogeneous

herding behavior

MG, N=101, S=2

25 - Complex System ’07 (Gold Coast)
Local Minority Games with Coupled Strategy

Minority games with neighbors

Payoff matrix of two agents

<table>
<thead>
<tr>
<th>Other agent</th>
<th>$S_1$</th>
<th>$S_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$S_2$</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Give-and-Take Rule

*(in contrast with win-stay, loose-shift)*

$p_i(t) < 0.5, a_i(t) = S_1 (Gain) \Rightarrow a_i(t + 1) = S_2$

$p_i(t) > 0.5, a_i(t) = S_2 (Gain) \Rightarrow a_i(t + 1) = S_1$

$p(t) : The \ proportion \ of \ agents \ choosing \ S_1$
Emergent Coordination in Local Minority Games

4 neighbors

8 neighbors

Agents

1 1000

1250

532

1 1000

1250

897

S1

S2

Generation After

N

N

27 - Complex System '07 (Gold Coast)
Synchronized Behavior and Emergence of Collective Intelligence

Initial configuration (random)

Neighborhood size = 4

Neighborhood size = 8

POA=1

<table>
<thead>
<tr>
<th>Other agent</th>
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<th>$S_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
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<tr>
<td>$S_2$</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

- Complex System '07 (Gold Coast)
Generalized Rock-Scissors-Paper Games

- $\lambda = 2$: Conventional R-S-P game
- $\lambda > 2$: Dispersion games

<table>
<thead>
<tr>
<th>Agent B</th>
<th>Agent A</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1 (Rock)</td>
<td>1</td>
</tr>
<tr>
<td>S2 (Scissor)</td>
<td>$\lambda$</td>
</tr>
<tr>
<td>S3 (Paper)</td>
<td>0</td>
</tr>
</tbody>
</table>

- A Nash equilibrium strategy: $(S_1: 1/3, S_2: 1/3, S_3: 1/3)$
- The expected payoff at Nash equilibrium: $(\lambda + 1)/3$
- Pareto-efficiency (average payoff): $\lambda/2$

But a winner gets, and loser gets nothing.
**Rock-Scissors-Paper Games on the Lattice(1)**

Co-existence of competing species: Kerr et al. (2002) demonstrated spatial structure allows biodiversity using RSP game

Evolutionary Process: A pair plays Rock-Paper-Scissors, and winner replaces loser

- **R + P→2P** (Paper wins and increases one more paper)
- **P + S→2S** (Scissors wins and increases one more scissors)
- **S + R→2R** (Rock wins and increases one more rock)
Well-mixed model: two randomly chosen agents can be paired
Localized model: agents can only be paired with neighbors

Forming niches is not enough
For the study of emergence
## RSP Games with Coupled Strategy

### Coupled strategy choice
Strategy choice is driven by the outcomes of the joint actions.

### Evolution of coupling rule
Agents update the coupling rule by changing value of #.

<table>
<thead>
<tr>
<th>Own</th>
<th>Opponent</th>
<th>Next Strategy</th>
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<td>#</td>
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<tr>
<td>2</td>
<td>2</td>
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</table>

0: Rock,  
1: Scissor,  
2: Paper  
#: 0, 1 or 2
Simulation Results: $\lambda = 10$

Nash equilibrium: 3.3
Pareto-efficiency: 5
POA = 1.5

Error rate: 0%
Average Payoff: 2.8
Lowest Payoff: 1.9
Highest payoff: 3.99

(i) The average payoff per agent

(ii) The ratio of each strategy

The strategy population is close to Nash equilibrium

Error rate: 10%
Average Payoff: 4.0
Lowest Payoff: 0.49
Highest payoff: 0.43

POA: decreased from 1.5 to 1.2
What Did Agents Learn?

The rules of 2,500 agents were aggregated into 8 rules with some common values.

<table>
<thead>
<tr>
<th>Rule Type</th>
<th>00</th>
<th>01</th>
<th>02</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>20</th>
<th>21</th>
<th>22</th>
<th>Number of Agents with the Same Rule</th>
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<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>10</td>
</tr>
</tbody>
</table>
Phase Diagram of the Strategy Choices

They converge into the limiting cycle where desirable synchronization is emerged

Limiting cycle and turn-taking behavior

Initial State

Winning phase

Losing phase

00

01

02

01

02

22

20

20

02

00

Win win

Lose lose

Draw draw

Limiting cycle

Win

Lose
Social Interaction: Type 3

Type 3: Mixture of coordination and dispersion
Economics: Tug-of-war between increasing returns and decreasing returns
Human behavior: Reconcile the tension between centripetal and centrifugal

Close, but not too close
BOID Model: Flocking Formation

Craig W. Reynolds (1994)

Flocking Behavior emerges with three coupling rules

- **Cohesion**: Head for the perceived center of mass of the neighbors.
- **Separation**: Don't get too close to any neighbor or object.
- **Alignment**: Try to match the speed and direction of nearby neighbors.
Flocking: Social Atomic View

Vicsek considered consensus problem, and found the phase transition in flocking

Flocking with Adaptive Coupling Rules

Case 1
Separate flocks

Case 2
Reformed flock

Task: obstacle avoidance while sustaining flock

Flocking Behavior: Agent’s View

Force of an agent

\[ \vec{F}_{fi} = \vec{F}_{ci} + \vec{F}_{si} + \vec{F}_{ai} = \left( W_c - \frac{W_s}{D} \right) \vec{e}_D + W_a \vec{e}_V \]

Adaptive cohesion & separation

(combine attractive force and repulsive force)

Force

\[ \vec{F}_{csi} = \left( W_c - \frac{W_s}{D} \right) \vec{e}_D \]

the sum of the position vector

\[ t \to \infty \Rightarrow D = \sum_j \vec{d}_{ij} \Rightarrow \frac{W_s}{W_c} \]

\[ \phi_{fi} = W_c D - W_s \log D \]

Secret of Emergent flocking:
Self-control with implicit potential function

Consensus: the sum of the relative velocity vector

\[ t \to \infty \Rightarrow V = \sum_j \vec{v}_{ij} \to 0 \]
Self-interest vs. Mutual Benefit

- Self-interested agents are faced with the dilemma of acting in their own interest or pursuing a more cooperative action in social contexts.

- A challenging task is to identify conditions under which agents are more coordinated than they are acting in their own interest.
Secret of Emergent intelligence: Better ways of couplings
: Coupling with aggregates (micro-macro loop)
: Coupling with neighbors

Coupled evolutionary dynamics would work for better coordination with mutual benefits
Concluding Remarks (1): Five Stages of Research

1) **Observe:** Gather data to demonstrate power law behavior in a system.

2) **Interpret:** Explain the import of this observation in the system context.

3) **Model:** Propose an underlying model for the observed behavior of the system.

4) **Validate:** Find data to validate (and if necessary specialize or modify) the model.

5) **Control:** Design ways to control and modify the underlying behavior of the system based on the model.

*Focus on control issues (guidance):* Lots of open research problems in the study of complex systems
Concluding Remarks (2): Challenging Issues

How to control smarter agents using ICT
(ICT: Information/Communication Technology)

- Smart intersections
- Smart highways
- Smart ‘skyways’
- Smart dispatch of urban emergency vehicles
- Smart routing of people and vehicles

- Smart agents often change their behaviors by getting information on the aggregate using ICT

- Congestion controls in a networked world should receive much attention
Final Remark

Scale

High

Socio physics
(Complex networks)

Complex adaptive systems

Smart agents in a connected world

Low

Self-interest seeking
Adaptability

Low

Social atom

Selfish agent

High

Multi-agent systems

Game theory
Thank you for listening!!