AGENT-BASED MODELING

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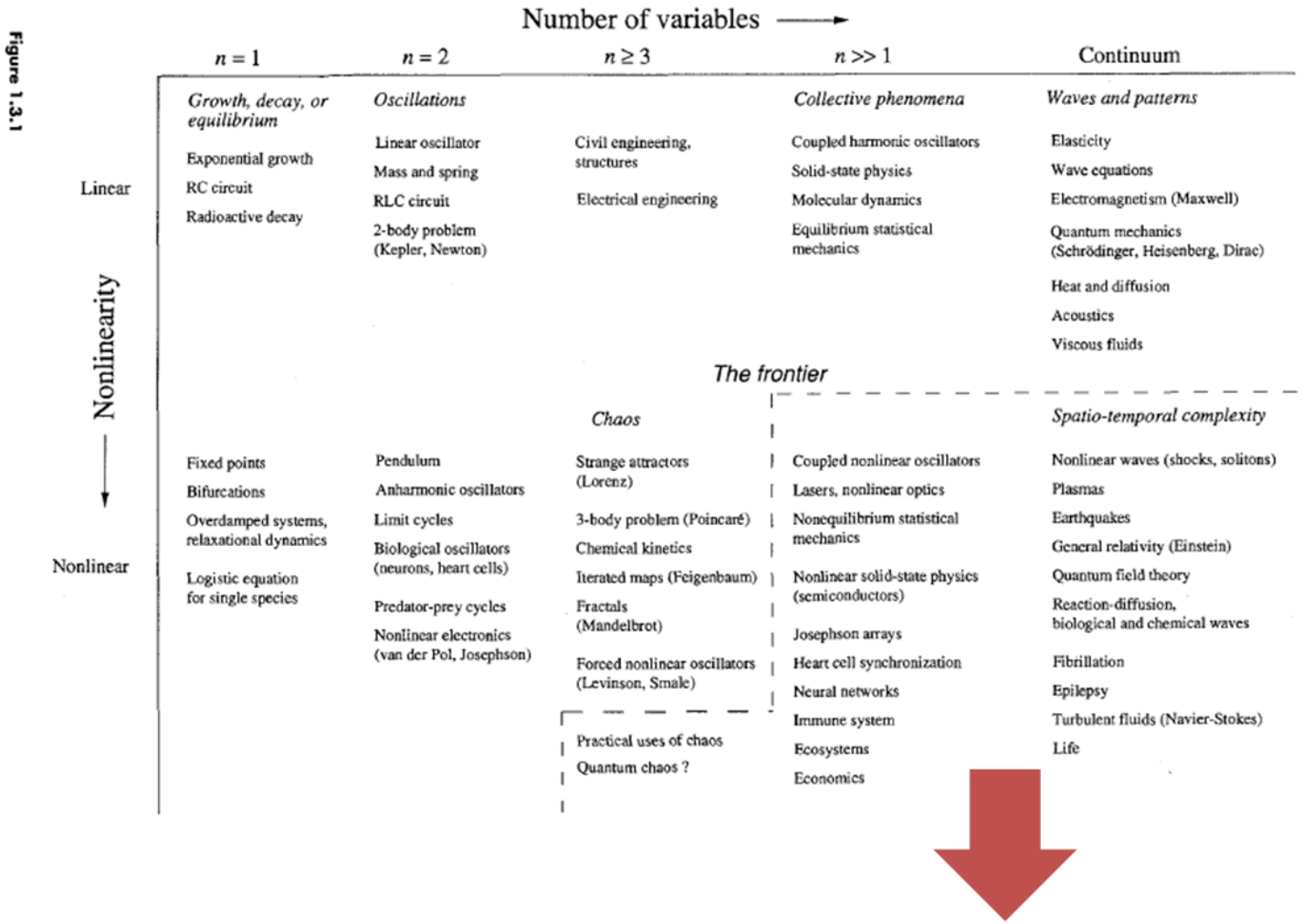
THE 'WHY'

"The study of non-linear functions is

akin to the study of non-elephants"

(Von Neumann)



Here be dragons!!

MOST INTERESTING SOCIAL SCIENCE PROBLEMS CAN BE DESCRIBED AS COMPLEX SYSTEMS

Systems with a large number of interacting parts, evolving over time and characterized by emergent **global** patterns from *local* interactions and decisions

Agent-Based Modeling (ABM) starts with the idea that the (social) world can be modeled by using a multiplicity of distributed agents, each following simple rules of behavior

Where an agent is an autonomous individual element endowed with properties and actions, in a computer simulation

SCHELLING'S SEGREGATION MODEL

https://www.netlogoweb.org/launch#https://www.netlogoweb.org/assets/modelslib/Sample%20Models/Social%20Science/Segregation.nlogo

Two types of agents: either poor or rich, either natives vs immigrants

+ homes unoccupied.

A person has 8 neighbours (centre of an 3x3 grid). At time t makes the decision to move f(surrounding neighbours).

- If (% similar neighbours is < Threshold (T)) move

Global patterns emerge from *local* interactions and decisions!

Macro-level behavior is linked to but not trivial to infer from micro level behavior

THIRD WAY OF DOING SCIENCE

1) induction – reasoning from data to theory

2) deduction – reasoning from first principles to theory

3) a third way – "[ABM] starts with a set of explicit assumptions (people will move when a certain threshold is met). But unlike deduction, it [ABM] does not prove theorems. Instead, simulation generates data that can be analyzed inductively." (Axelrod, 1997)

- A computational thought experiment

WHAT CAN YOU DO WITH IT?

creativity and innovation management

REGULAR ARTICLE | Full Access

The IKEA effect in collective problem-solving: When individuals prioritize their own solutions

Oana Vuculescu, Michela Beretta, Carsten Bergenholtz

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THE RESEARCH IN BRIEF

RQ: How should collectives be organized, to optimize collective problem solving?

Prior empirical and simulation work leads to mixed results> e.g. Lazer and Friendman (2007) argue that fully connected networks are detrimental to performance, while Mason and Watts (2012) find that managers should prioritize the efficient networks (i.e. fully connected) to maximize performance.

Methods: Agent-based simulation model—6 key parameters

i) 100 agents search an NK landscape (N=20, K=0, 1, 6)
ii) Efficient vs. inefficient networks (Watts & Strogatz 1998)
iii)First social learning, then individual search
iv)Ikea-effect of 10% added to agent's own solution
v) Perfect imitation vs. randomly copying (Axelrod 1997)
vi)Greedy vs. non-greedy local search

RESULTS

Ikea-effect (10% premium on own solution) increases CPS performance

CPS performance: # of times the maximum is reached by an individual agent

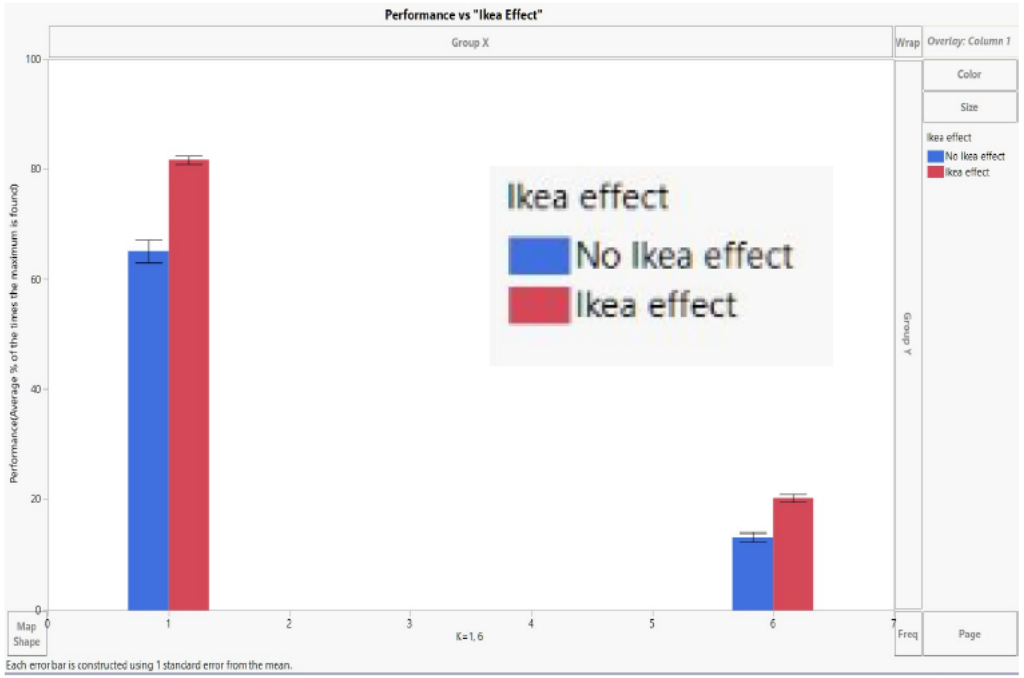

Fig. 1. Average performance across all experimental conditions. Experiments were replicated 100 times for each combination of parameters (2800 runs). We report results for a relatively simple (K=1) vs. a relatively complex (K = 6) problem. Allowing for an individual bias towards a focal agent's own solution (i.e. encountered solutions would have to be at least 10% better than current best to lead to copying) result in an overall improved performance, irrespective of other chosen parameters (i.e. type of network, number of peers one can "observe" before moving to individual search, type of local search, type of social learning).

In efficient networks, if Ikea-effect —> more local search, i.e. fewer premature jumps from potential good solutions due to social learning

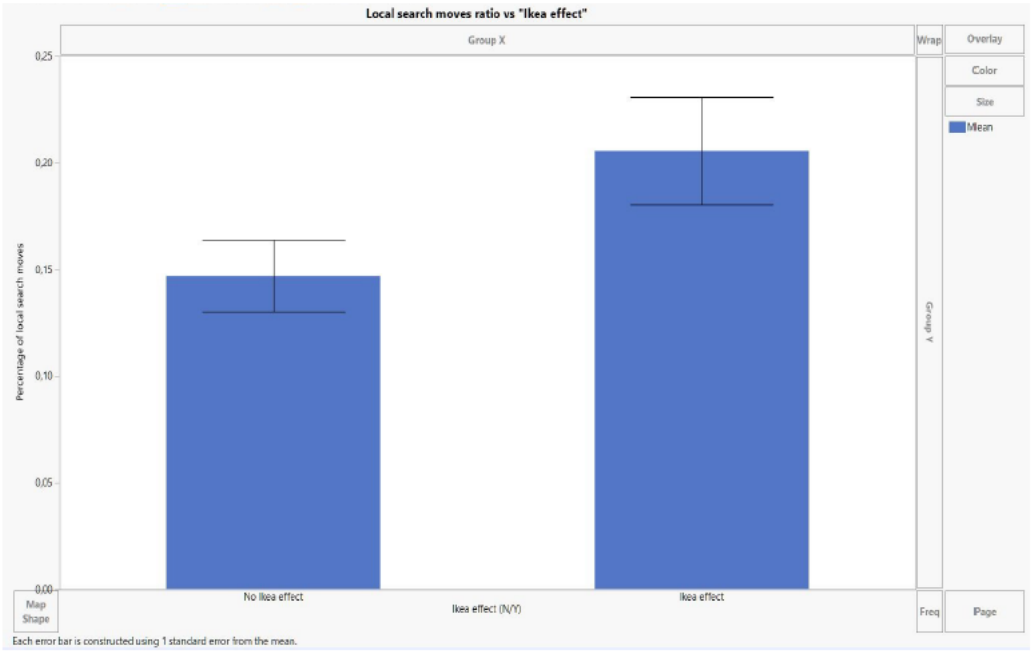

Fig. 2. Average percentage of local search moves for K=6, fully connected networks. Experiments were replicated 100 times for each combination of parameters (40 *100 runs).

CHALLENGES

1) social acceptance – depending on field - 'your model is tautological' critique (yes, so is all of math)

2) validation - "Ideally, ABMs should be validated at both the level of interactions between agents and the aggregate behavior that they generate, comparing interactions and aggregate behavior with empirical relational magnitudes and state magnitudes, respectively." (Fioretti 2013) – but we don't always have 'clean' micro level data, nor do we always agree on what the aggregate behavior looks like

3) (socio) technical challenges – community, tools/frameworks, speed

USEFUL REFERENCES

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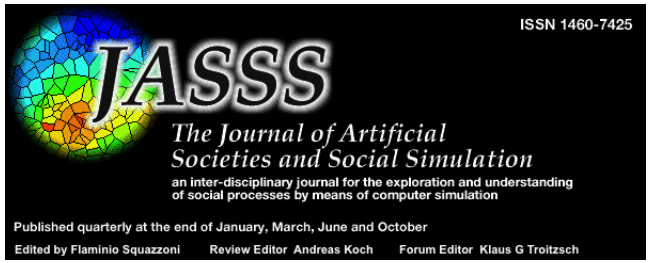
RESOURCES - COMMUNITY

- SFI – Summer School
- ESSA – Summer School, Conference
- JASSS – Journals

SANTA FE INSTITUTE



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