Computational Modeling of Social Systems

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About the teaching team

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- Faculty member and group leader at the Complexity Science Hub Vienna

Petar Jerčić

- Postdoctoral researcher at CSS lab

Pavle Savković
- Teaching assistant and CSS master student

Overview

1. Why models? Complex Social Behavior
2. Agent-Based Modelling (ABM)
3. ABM Example: Date Choice Model
4. About this Course

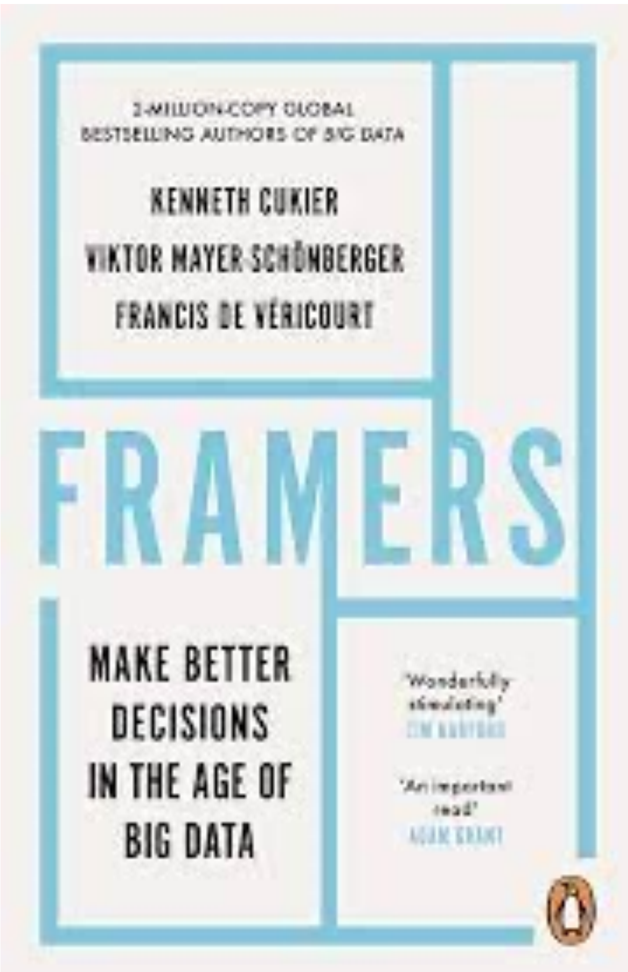
Why models?

Models are the construction of reality and a way of explaining what we see in the world.

Without models, we can’t explain why we see what we see. Models make us smarter and help us not only understand the world but also say something about the future or even build the future

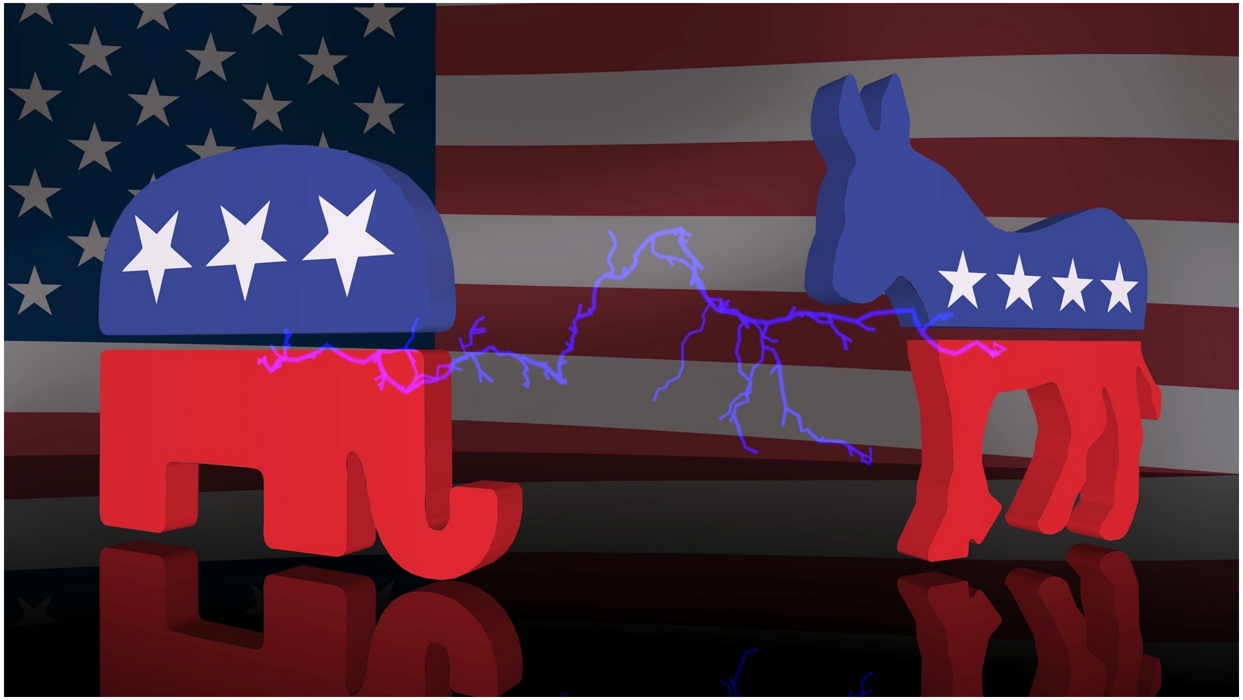
In a broader sense, model thinking allows us to frame the world, make logical connections, and also reframe the world.

Model thinking helps us become framers



Framers is defined by the idea that when we "frame" something, we "create a mental model enabling us to see patterns," almost able to see into the future of our ideas.

Complex social behvior: extreme opinion and polarization



- Two opposing groups can become more extreme due to their perception of the behavior and opinions of the other group.
- Individuals in isolation do not naturally tend to have extreme opinions.

Complex social behavior example: Bank runs

A run on a bank of East Asia branch in Hong Kong, caused by "malicious rumours" in 2008

- Banks operate without all the savings in their reserves
- If customers believe that many others withdraw their money, they will do it too
- The rumor and spreading distrust results in a bank run (**the tragedy of the commons**)
- Would customers in isolation create a bank run??

Tragedy of the commons/social traps/social dilemmas

PLOS ONE

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Simulating Irrational Human Behavior to Prevent Resource Depletion

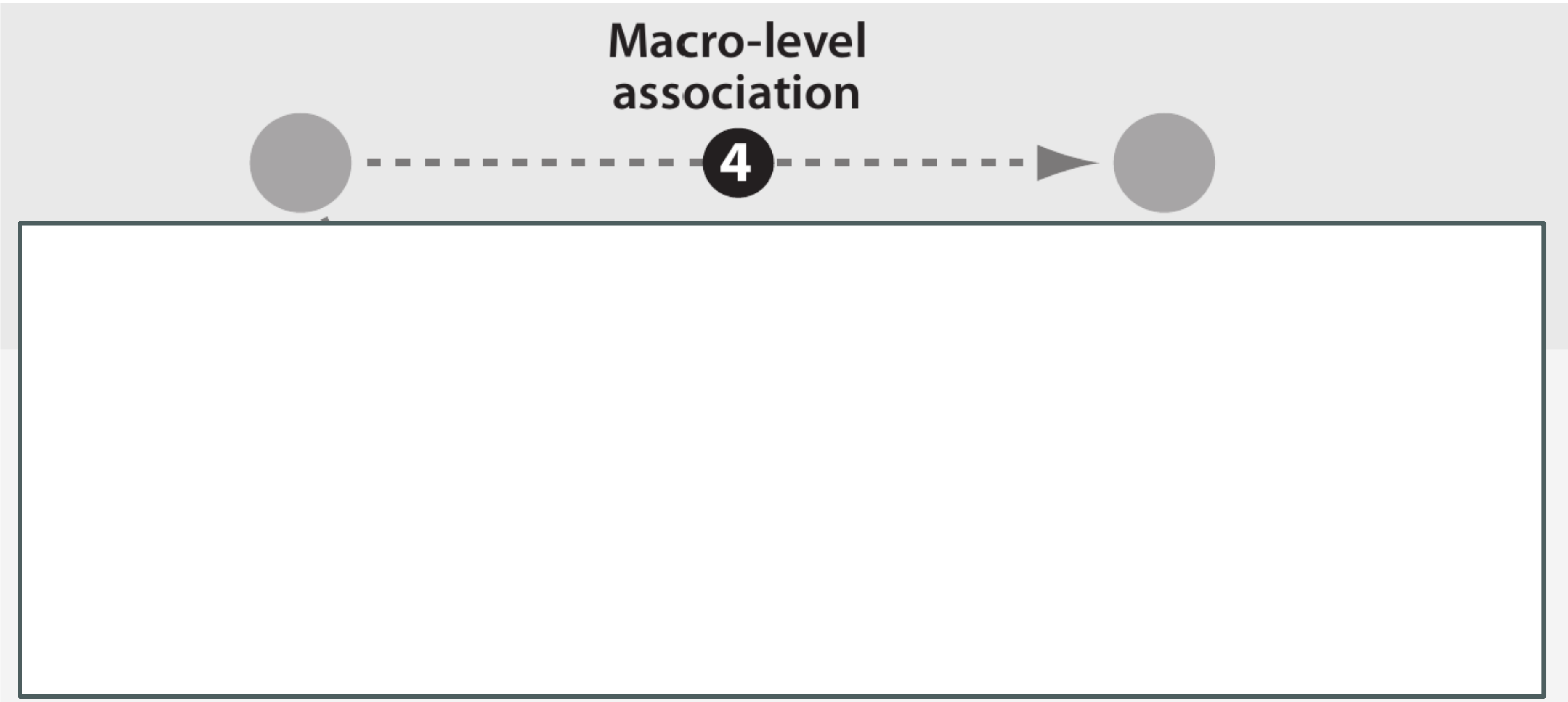
Anna Sircova, Fariba Karimi, Evgeny N. Osin, Sungmin Lee, Petter Holme, Daniel Strömbom

Published: March 11, 2015 • https://doi.org/10.1371/journal.pone.0117612

Complex social behaviors: Activation and inhibition

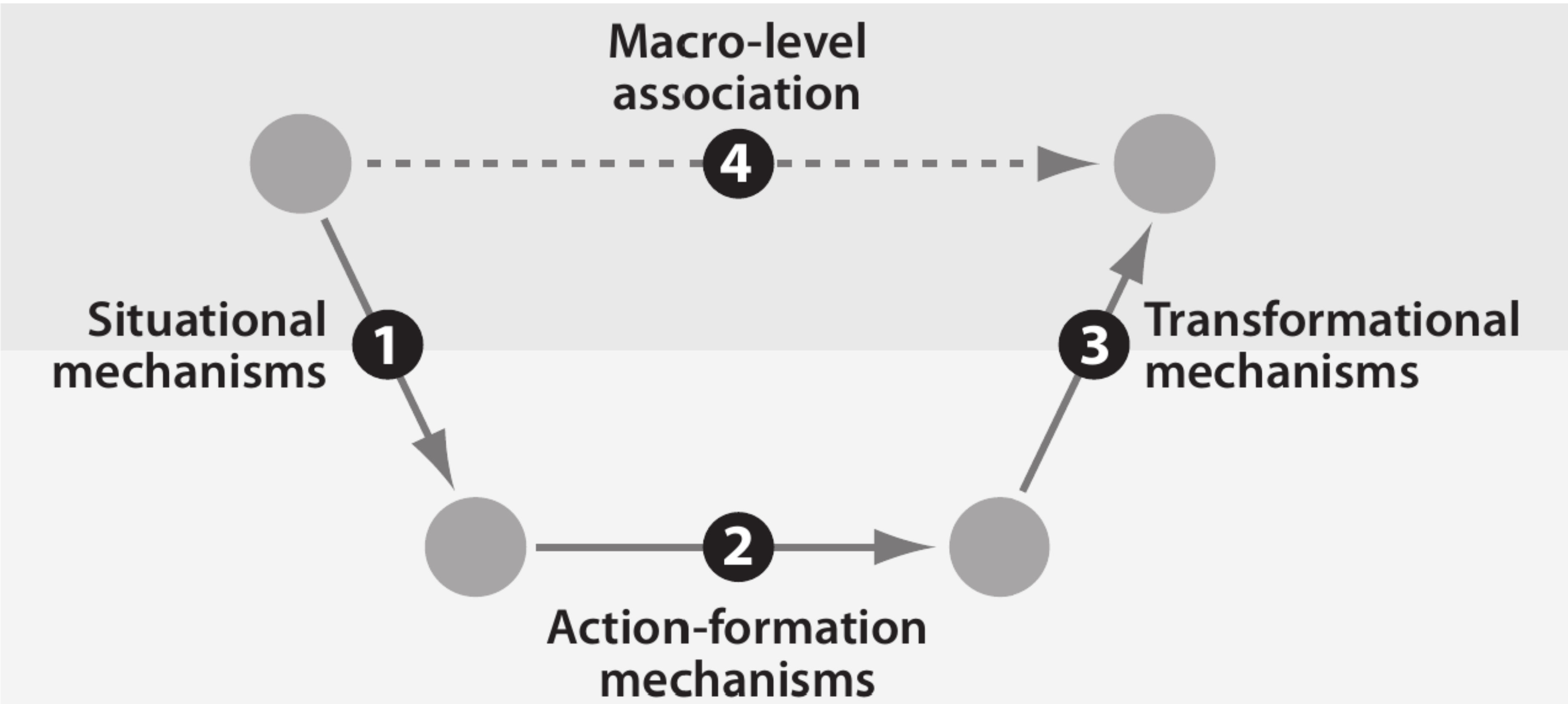
- Individuals demonstrating in isolation are peaceful, but in a group a riot can emerge without a clear antecedent
- People alone in the street offer help, but when many are watching they don't act (**bystander effect**)

The micro-macro gap



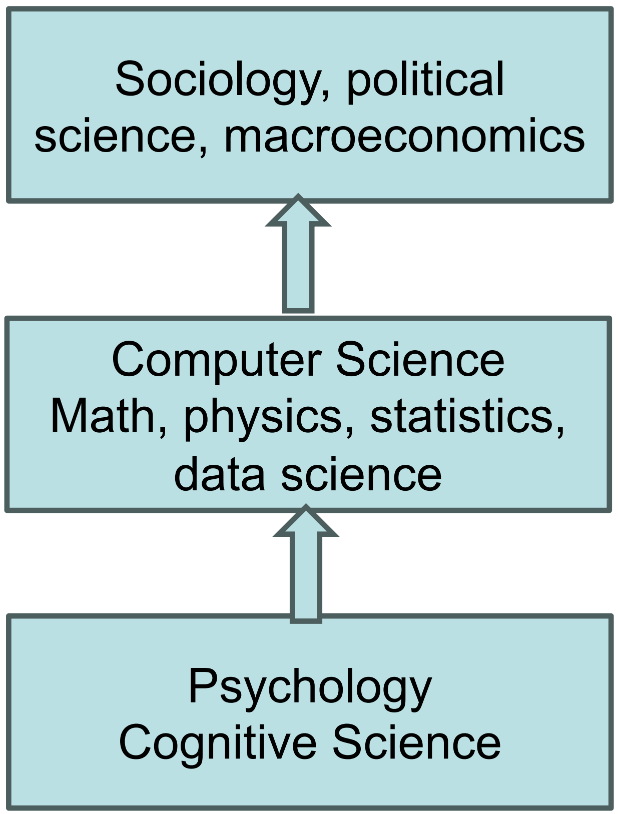
Causal Mechanisms in the Social Sciences. Peter Hedström and Petri Ylikoski. Annual Review of Sociology, 2010.

The micro-macro gap



Causal Mechanisms in the Social Sciences. Peter Hedström and Petri Ylikoski. Annual Review of Sociology, 2010.

Interdisciplinarity in complex social behavior



Norms, institutions, inequality, conflict

Simulations, networks, dynamical systems

Opinions, emotions, beliefs, social contacts

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1. Why models? Complex Social Behavior
2. Agent-Based Modelling (ABM)

Agent-Based Modelling (ABM)

•Agent-Based Model: A computational analogy of a social system that is composed of a set of agents (actors) that represent *discrete* individuals

•Agents have internal states, perceive the actions of other agents, and interact with other agents and their environment (*situated*)

•Agents are *active*: they have a behavioral repertoire, they are not just particles

•Agents might have access only to *limited information* in their environment

•Agents might have *internal goals* that determine their behavior and can *adapt to* the behavior of other agents or the environment

Agent-Based Modeling: A New Approach for Theory Building in Social Psychology. Eliot Smith and Frederica Conrey, 2007

Steinbacher et al. "Advances in the agent-based modeling of economic and social behavior." SN Business & Economics 1.7 (2021): 99.

Explaining behavior with ABM

- Observed collective behavior or effects are *explananda*: empirical facts that are missing an explanation.
    - Example: hotter days have higher average crime rates
- ABM offers *explanations*: theories that generate the observed behavior and link it to other empirical facts
    - Example: heat makes people spend longer in the street, facilitating crime
- ABM is part of a larger theoretical approach called *Analytical Sociology*, where everything in a model of social behavior must be explicit
    - Example: coding a simulation of people going out depending on temperature and crimes happening outdoors as a function of more people interacting

Explaining behavior with ABM

Are simulation results alone evidence that humans behave in one way or another?

Explaining behavior with ABM

ABM do not provide empirical evidence

• Simulation results alone are not evidence that humans behave in one way or another. Beware of causal conclusions based on ABM alone!

• They can **generate hypotheses**, for example, on the consequences of policies in simulations or formulate predictions

• They can **reconcile empirical observations** across individual behavior and collective behavior levels

•They are a way to **analyze theory**, showing necessary or sufficient conditions for some collective behavior to emerge

Beyond exploration: computational theory and framing

ABM are for analysis, not just exploration

• Exploring what happens in a simulation is fine, but ABM can do much more!

• **Behavior calibration** of individual agents with experiments or surveys: integrating social and behavioral findings in an ABM

• **Analysis of observable outcomes** versus parameters of behavior or alternative mechanisms/policies

• **Testing outcomes** with large-scale data (e.g. digital traces from computational social systems), across conditions and over time

From factors to actors: Computational Sociology and Agent-Based Modeling. Michael Macy and Robert Willer. Annual Review of Sociology, 2002.

Properties of good ABM

•They **model causation**: agent actions and conditions have counterfactuals, and dynamics are not ad hoc to get an outcome

Counterfactual: expressing what has not happened but could, would, or might under differing conditions.

•They have **measurable outcomes:** collective behavior can be aggregated into one or more quantities that can be measured in many simulations and across conditions

•They have **quantifiable designs:** individual dynamics are based on metrics that can be tested with empirical methods (e.g. experiments, surveys)

•Are **minimal and modular:** you can test the sensitivity of outcomes with different blocks of dynamics and include only what is necessary

Ockham's razor principle: if you have two competing ideas to explain the same phenomenon, you should prefer the simpler one.

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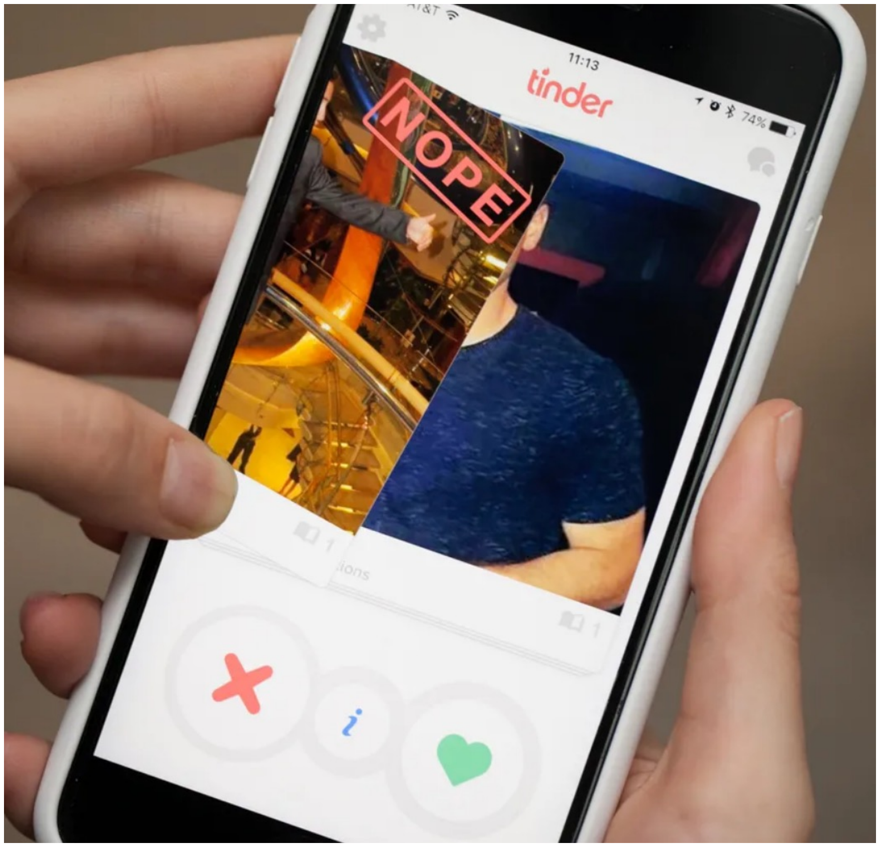
Dating choice



tinder!

Tender!

The question of attractiveness matching

• Example: Kalick and Hamilton (1986) date choice model

• **Question**: do people seek dating mates that are as attractive as possible or matching their own perceived attractiveness?

• **Conflicting evidence**:

- In experiments (micro), participants seek to maximize partner attractiveness; participant attractiveness is barely relevant

- In observational data (macro), the attractiveness of couples is correlated
($r \sim 0.6$) and correlation is stronger for more committed couples

The matching hypothesis reexamined. Michael Kalick and Thomas Hamilton. Journal of Personality and Social Psychology, 1986.

The dating model

How would you model this to consolidate these two competing hypotheses?

Work in group of 2; 15 min

The Kalick and Hamilton dating model

•Start with N male and N female agents, all are uncoupled

•Each agent has a constant attractiveness number randomly sampled between 1 and 10 at the beginning of the simulation

•Repeat while there are uncoupled agents:

- All male and female agents are randomly paired for a date
- Dates consist on each individual accepting or rejecting their partner. The probability of accept is based on a rule taking into account their attractiveness levels (e.g. matching or seeking attractiveness)
- Dates with both agents accepting form a couple and leave the dating pool

Model metrics

1. Model "time" t: Percentage of agents that are in a couple
   - It grows with simulation iterations, starting from 0 and approaching 100
2. Correlation coefficient between paired couples (r_t) at time t:

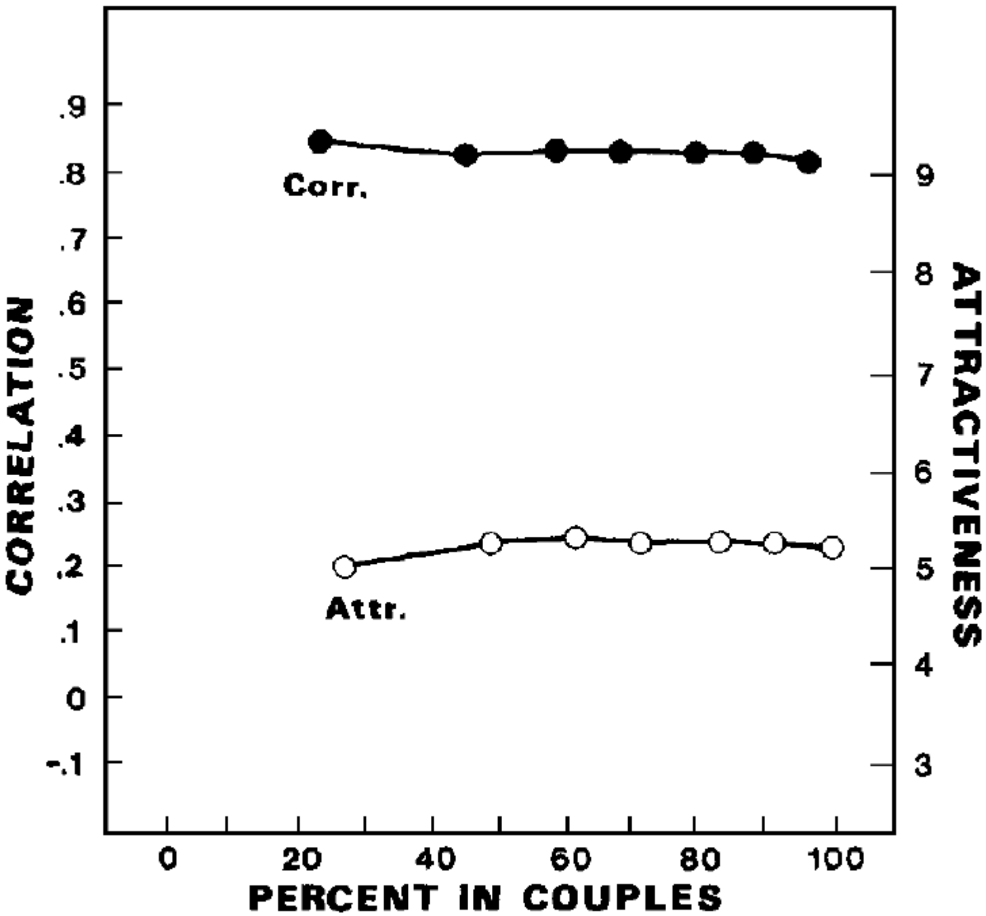
$$r_t = r(M_t, F_t) = \frac{\sum_{c \in C_t} (m_c - \mu_{M_t})(f_c - \mu_{F_t})}{\sqrt{\sum_{c \in C_t} (m_c - \mu_{M_t})^2 (f_c - \mu_{F_t})^2}}$$

   - M_t and F_t are the vectors of male and female attractiveness in couples formed up to time t, denoted as Ct

3. Mean attractiveness of the N_t paired couples at time t:

$$\mu_t = \mu_{M_t} + \mu_{F_t} = \sum_{c \in C_t} (m_c + f_c) / N_t$$

Seeking similar match: outcomes

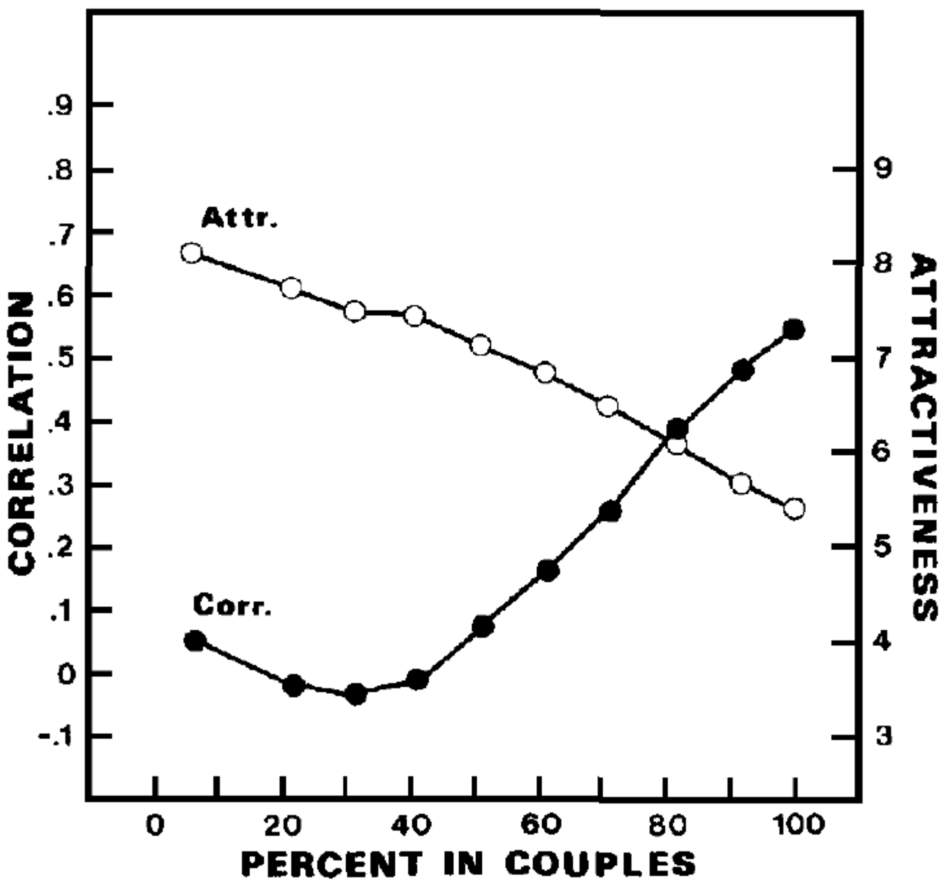


•Outcomes over simulation time (% matched couples) for the case of seeking similar partners
•Correlation starts very high (0.8)

. No real trend in correlation

. Mean couple attractiveness is around the average the whole simulation

Maximizing partner attractiveness



- Outcomes over simulation time (% matched couples) for the case of preferring attractive partners regardless of own attractiveness

- Correlation starts low but raises pretty fast up to about 0.55

- Mean couple attractiveness starts much above average and approaches average

- Attractive agents couple earlier

Results of dating model

•**Main result:** attractiveness matching is not necessary for observed correlations, they can be produced by attractiveness seeking alone.

•ABM reconciles apparently conflicting empirical results

•**Comparison with empirical data:** observed empirical correlation is closer to 0.55 than to 0.9

- This could also be due to measurement error in attractiveness

•**Many simplifications**

The matching hypothesis reexamined. Michael Kalick and Thomas Hamilton. Journal of Personality and Social Psychology, 1986.

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Course objectives

1. Understanding how to **formulate and analyze** computational models of social systems.

2. Integrating knowledge about social dynamics and analytic tools to understand the **complex behavior** of social systems.

3. Acquiring programming skills to **implement, simulate, and visualize** computational models of social systems

Course topics:

Block 1: Fundamentals of agent-based modelling

1- **Basics of agent-based modeling: the micro-macro gap**

Tutorial: ABM basics in Python with Mesa (session 1)
(Please install Jupyter and iPython as soon as possible)

2- **Modelling segregation: Schelling's model**
Tutorial: ABM basics in Python with Mesa (session 2)

3- **Modelling cultures**
Exercise 1: Schelling's model and Pandas (session 1)

Course topics:

Block 2: Opinion dynamics

4- Basics of spreading: Granovetter's threshold model
Exercise 1: Schelling's model and Pandas (session 2)

5- **Opinion dynamics**
Exercise 2: Threshold models (session 1)

6- **Information spreading dynamics**
Guest lecture by Prof. Jana Lasser
Exercise 2: Threshold models (session 2)

No class between 25.03.2024 and 07.04.2024: ***Easter holidays***

Course topics:

Block 3: Network formation

7- **Basic network models**
Exercise 3: Bounded confidence (session 1)

8- **Modelling small worlds**
Exercise 3: Bounded confidence (session 2)

9- **Scale-free networks**
Exercise 4: Scale-free networks and visualization (session 1)

Course topics:

Block 4: Network formation

10 - Game theory I
Project guidance

11 - Game theory II
Project guidance

No class on 12.06; Project work

12- Project final presentations

13- Project final presentations

Time, place

•Lecture time: Wednesdays at 15:00 (sharp)
Lecture place: **HS A (NT01004)**

• Exercise group 18:00 – 19:00 **HS E (NT01088)**

•Handouts, codes, and data can be found on the Github repository of the course: github ComputationalModellingSocialSytems2024

1-2 readings for each lecture: Links on github and PDF on Teach Center Computational Modelling of Social Systems

Suggested inspirations for modeling exercise and final presentation