UNIVERSITÄT KONSTANZ

The Basics of Agent-Based Modeling

Computational Modelling of Social Systems

Giordano De Marzo
Max Pellert

About Me

- Postdoc at the Political Science department, University of Konstanz
- Junior Research Fellow at Complexity Science Hub Vienna
- PhD in Physics at Sapienza University (Rome) and Enrico Fermi Research Center
- MSc and BSc in Theoretical Physics at Sapienza University (Rome)

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View from my room at Enrico Fermi Research Center

About Me

- Complex Digital Systems
- Social Networks
- Recommendation Algorithms
- Economic Complexity
- Artificial Neural Networks
- Large Language Models

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About Prof. Max Pellert

- Professor for Social and Behavioural Data Science (interim, W2) at the University of Konstanz
- Assistant Professor (Business School of the University of Mannheim)
- Worked in industry at SONY CSL in Rome, Italy
- PhD from the CSHVienna and the Medical University of Vienna in Computational Social Science
- Studies in Psychology and History and Philosophy of Science
- MSc in Cognitive Science and BSc in Economics (both University of Vienna)

About Prof. Max Pellert

Research interests:

- Computational Social Science
- Digital traces
- Affective expression in text
- Natural Language Processing
- Collective emotions
- Belief updating
- Psychometrics of AI

Outline

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

About this Course

Course Objectives

Upon the completion of this course, students will be familiar with the following:

- Various approaches to **model social interactions** to bring the micro-macro gap
- General principles of **agent-based** modelling and **network** modelling
- The analytical approach to formalization, simulation, and analysis of **computational models**
- The role of empirical data in the **calibration** and **validation** of computational models
- The **limitations** and **applications** of computational modelling in the social sciences

Course **Format**

This course is structures in three different parts:

- 9 Theoretical seminars covering the basics of Agent Based Modeling and of Network Theory
- 4 Coding sessions with prof. Max Pellert
- 4 or 5 Students seminars sessions

The coding sessions are optional but strongly recommended!
The first coding session will be tomorrow.

Course **Assessment**

Students select a published article from a set of readings to present in the second part and to write a review of the article as final report.

The course grade is based on:

- the student **presentation** (50%)
- **participation** in discussions after each presentation (20%)
- and on the **report** (30%)

Coding is not necessary but reimplementing a model from a paper is a great start to present it. This is not a required step: some models might be too complicated or require unavailable data.

Suggested Papers for Exam

- You can check
  https://giordano-demarzo.github.io/teaching/computational-modeling/
  for article suggestions
- Choose by email to me and Prof. Pellert by 15/06.
- You can find your own paper too, but email me and Prof. Pellert for confirmation in advance.
- No paper can be presented by two students: First-come first-served.
- Your presentation date will be chosen at random and announced next week.
- Date swaps are allowed by agreement of both students.

Course Dates

April 9, 2024-The Basics of Agent-Based Modeling
April 16, 2024-Modelling segregation: Schelling's model
April 23, 2024-Modelling cultures: Axelrod's model
April 30, 2024-Basics of spreading: Granovetter's threshold model
May 7, 2024-Opinion dynamics
May 14, 2024-Modelling small worlds
May 21, 2024-Scale-free networks
June 4, 2024-Resilience in social networks
June 11, 2024 (?)-Growth processes and spreading in networks

Students Seminars following

Complex Social Behavior

Bank Runs Financial Crisis

Micro-Level

A single person can not cause a bank run or a financial crisis.

Macro-Level

If customers believe that many others withdraw their money the rumor and spreading distrust creates a bank run (tragedy of the commons).

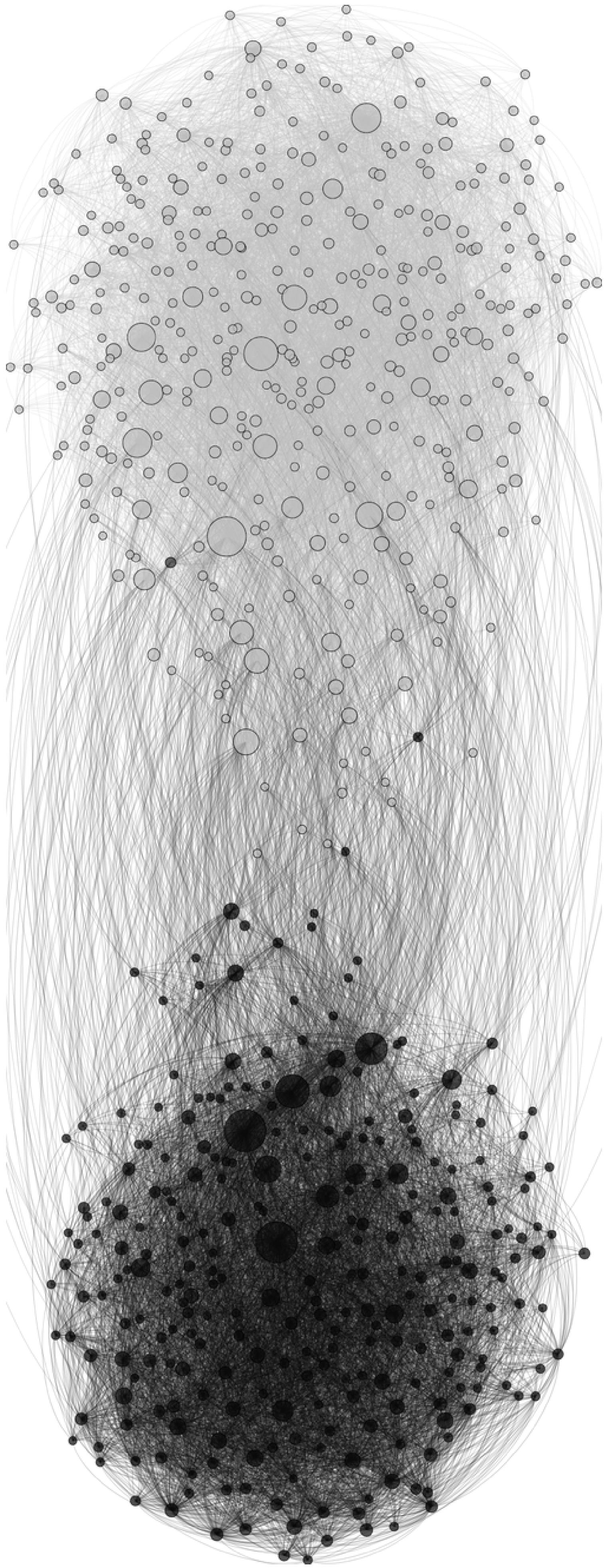
Social
Polarization

Micro-Level

Individuals in isolation do not naturally tend to opinion extremes.

Macro-Level

Two opposing groups can become more extreme due to their perception of the behavior and opinions of the other group.



Activation and Inhibition

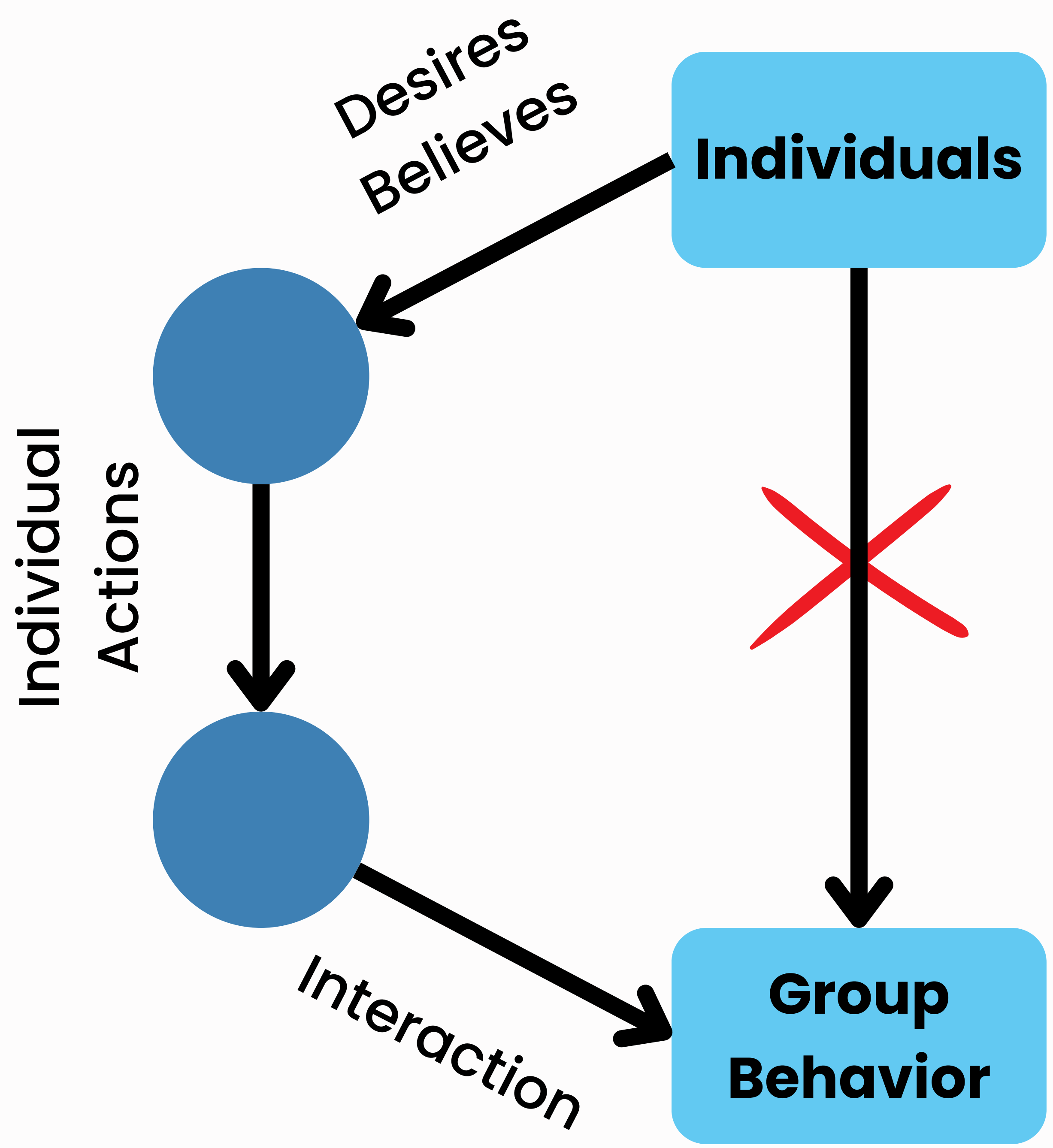
Micro-Level

Individuals demonstrating in isolation are peaceful and people alone in the street offer help.

Macro-Level

In a large group a riot can emerge without a clear antecedent. When many people are watching they don't offer help (bystander effect).

The Macro-Micro Gap



Emergent Phenomena

Complex (Social) Systems show spontaneous emergent behaviors that can be hardly directly linked to the microscopic components.

Ex. Cells vs molecules and atoms

Universality

Even if the microscopic components of Complex (Social) Systems may have specific features, these individual features are often barely relevant for the macroscopic behavior.

An Interdisciplinary Field

Individual Level → **Group Level**

Physiology, Cognitive Sci. → **Computer Sci., Math, Physics** → **Sociology, Political Sci., Economics**

- Opinions
- Emotions
- Believes
- Social Contacts

- Simulations
- Networks
- Dynamics Systems

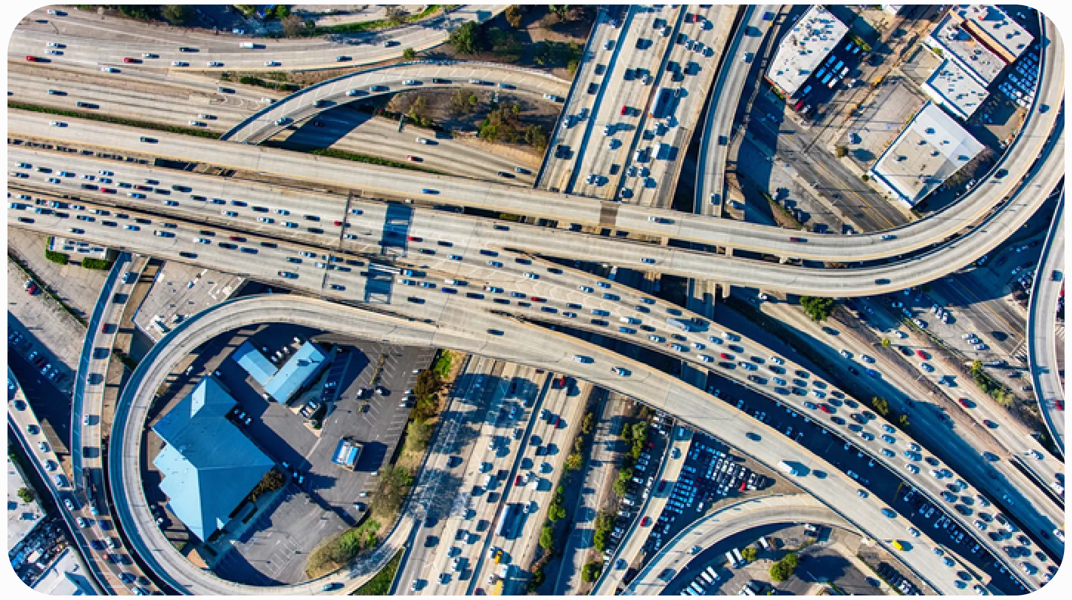
- Norms
- Institutions
- Polarization
- Inequality

Agent-Based Modelling (ABM)

What is an ABM?

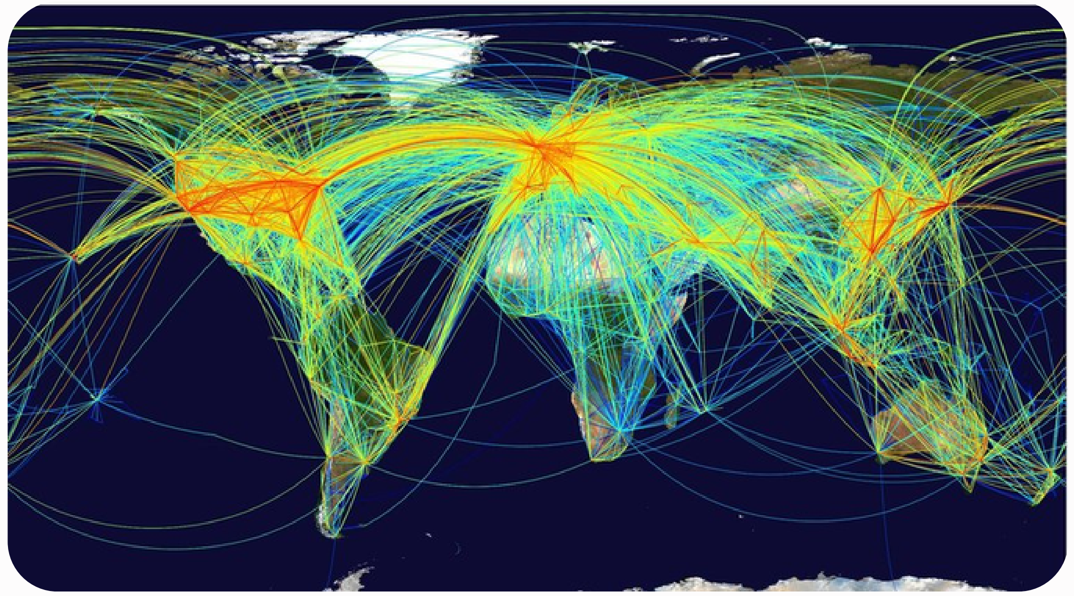
Agent-Based Model

A computational analogy of a social system that is composed of a set of agents that represent discrete individuals



Traffic and mobility

Supply Chains

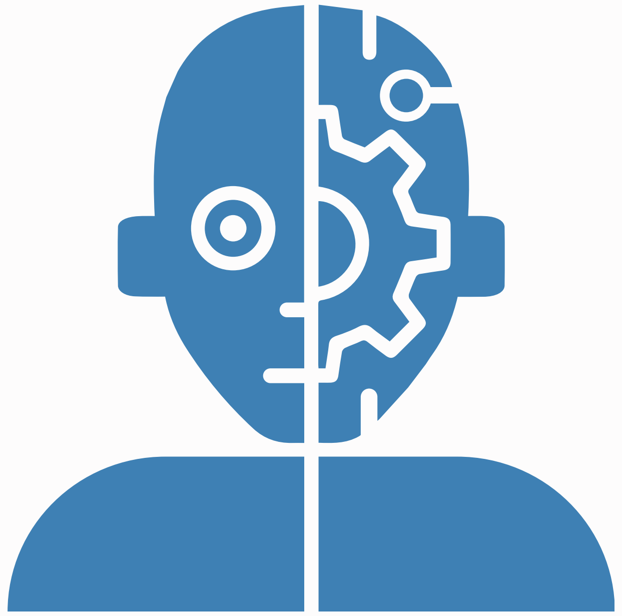


Epidemic Spreading

What is an Agent?

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, are not just particles. Often **probabilistic** rather than deterministic



Agents might have access only to **limited information** in their environment or information can be **manipulated**

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

Explaining Emergent Phenomena

Explananda

Observed **collective behavior** or effects are explananda: empirical facts that are missing an explanation.
Ex. Hotter days have higher average crime rates.

ABM

ABM offer explanations by linking the **macroscopic** group behavior to the **microscopical** individual mechanisms.
Ex. Heat makes people be longer in the street, facilitating crime

Analytical Sociology

ABM are part of a larger theoretical approach called **Analytical Sociology**, where everything in a model of social behavior must be explicit.
Ex. coding a simulation of people going out depending on temperature and crimes happening outdoors

ABMs Examples

Explananda	Spontaneous Traffic Jams	Global shortage of goods	Pandemics
Individual Level	Drivers in cars, trucks etc	Companies, warehouses etc.	Infected and healty people
ABM	A simulation of all vehicles	A simulation of the firm-firm interactions	A simulations of people spreading a virus

Traffic and mobility

Supply Chains

Epidemic Spreading

Limits and Uses of ABMs

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!

ABM can generate hypothese

They can generate hypotheses, for example on the consequences of policies in simulations or formulate predictions. ABM can therefore be tested.

ABM can close the micro-macro gap

They can reconcile empirical observations across individual behavior and collective behavior levels.

ABM help formulating theories

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

In Silico Social Experiments

ABM are for analysis and testing, 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
- **Testing outcomes** with large-scale data (e.g. digital traces from computational social systems), across conditions and over time
- **Prediction of observable outcomes** versus parameters of behavior or alternative mechanisms/policies

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

Fundamental properties of ABMs

Causation Modeling

Agent actions and conditions are grounded in observations and dynamics are not ad hoc to get the desired outcome.

Quantifiable Design

Individual dynamics are based on metrics that can be tested with empirical methods (e.g. experiments, surveys).

Measurable Outcomes

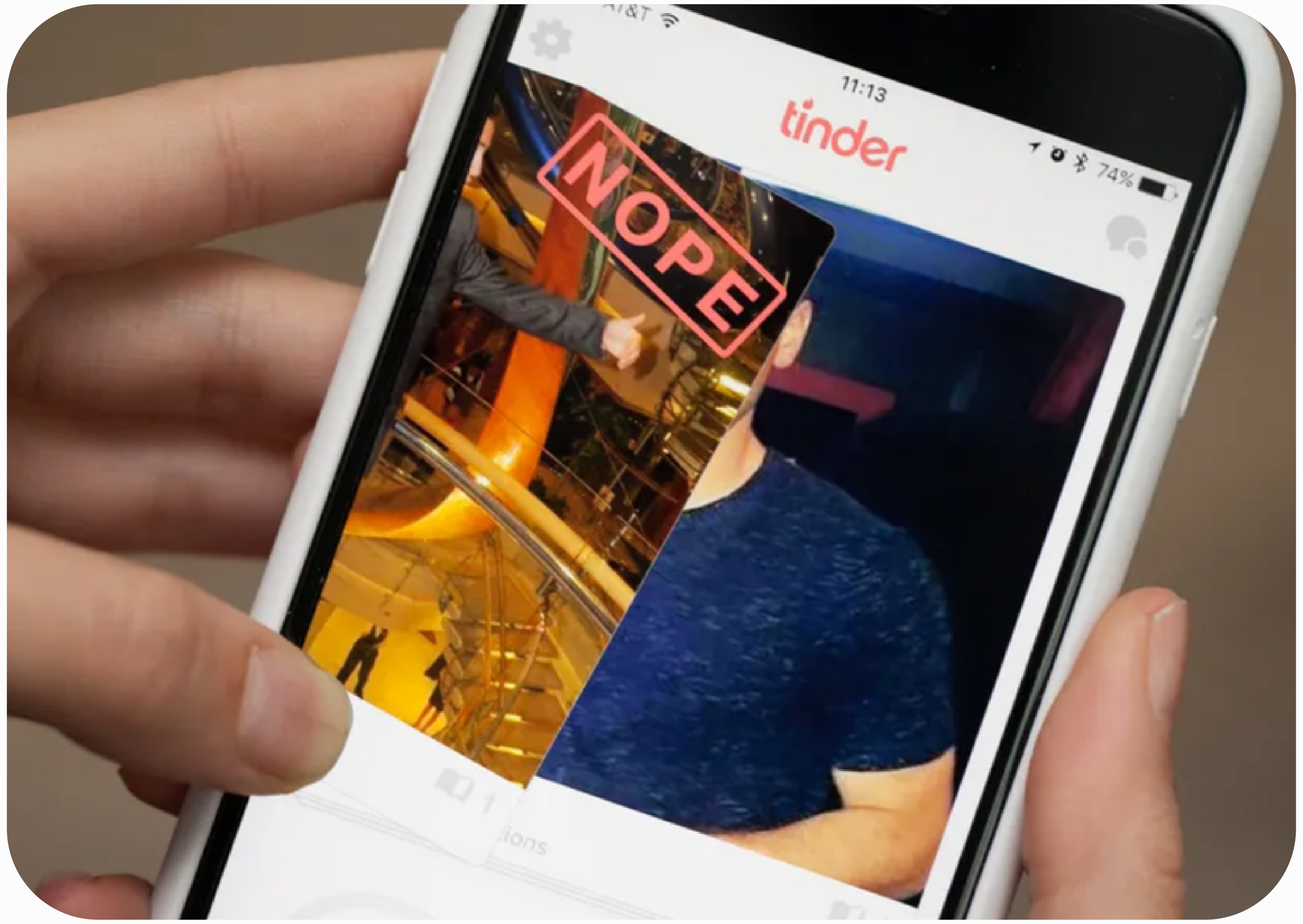
Collective behavior can be aggregated into one or more quantities that can be measured in many simulations and across conditions.

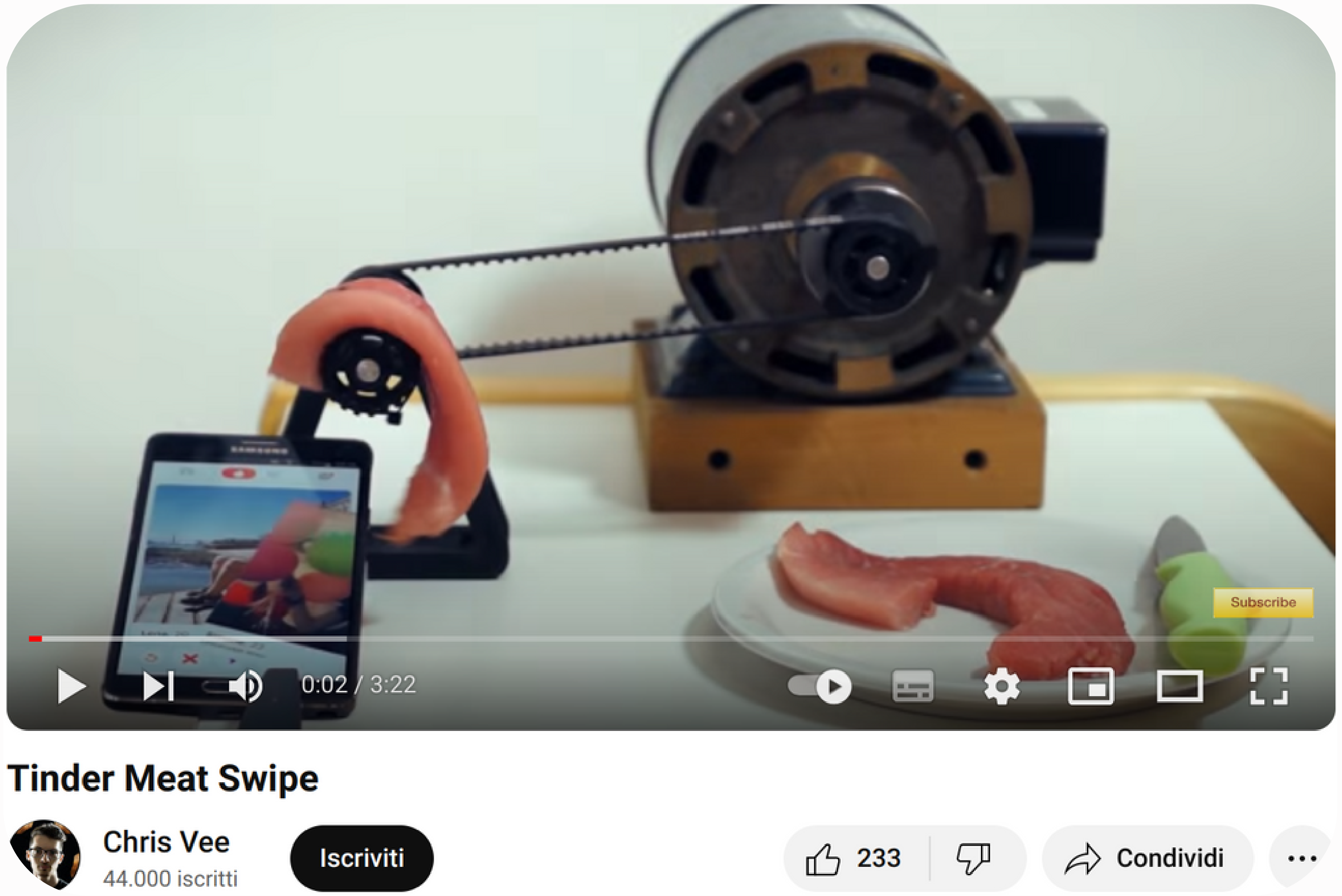
Minimality and Modularity

The ABM can be divided into different blocks describing different properties and interactions among the individuals. Only the minimal, necessary features must be included.

Date Choice Model

Date Choice in Computational Social Systems





The Matching Paradox

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

There is conflicting evidence!

- **Individual Level** In experiments participants seek to maximize partner attractiveness, participant attractiveness is barely relevant
- **Group Level** In observational data attractiveness of couples are correlated (r   0.6) and correlation is stronger for more committed couples

Kalick and Hamilton dating model

The model is defined as follows:

- There are N **female** and N **male** agents
- Each agent has a **random attractiveness** between 1 and 10
- Couples are formed by an **iterative process:**
    a. All single male and female agents are **randomly paired** for a date
    b. Each individual accept or reject their partner with a **probability** based on a rule taking into account their attractiveness levels (e.g. matching or seeking attractiveness)
    c. If both agents accept they form a couple and **leave** the dating pool

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

Model Metrics

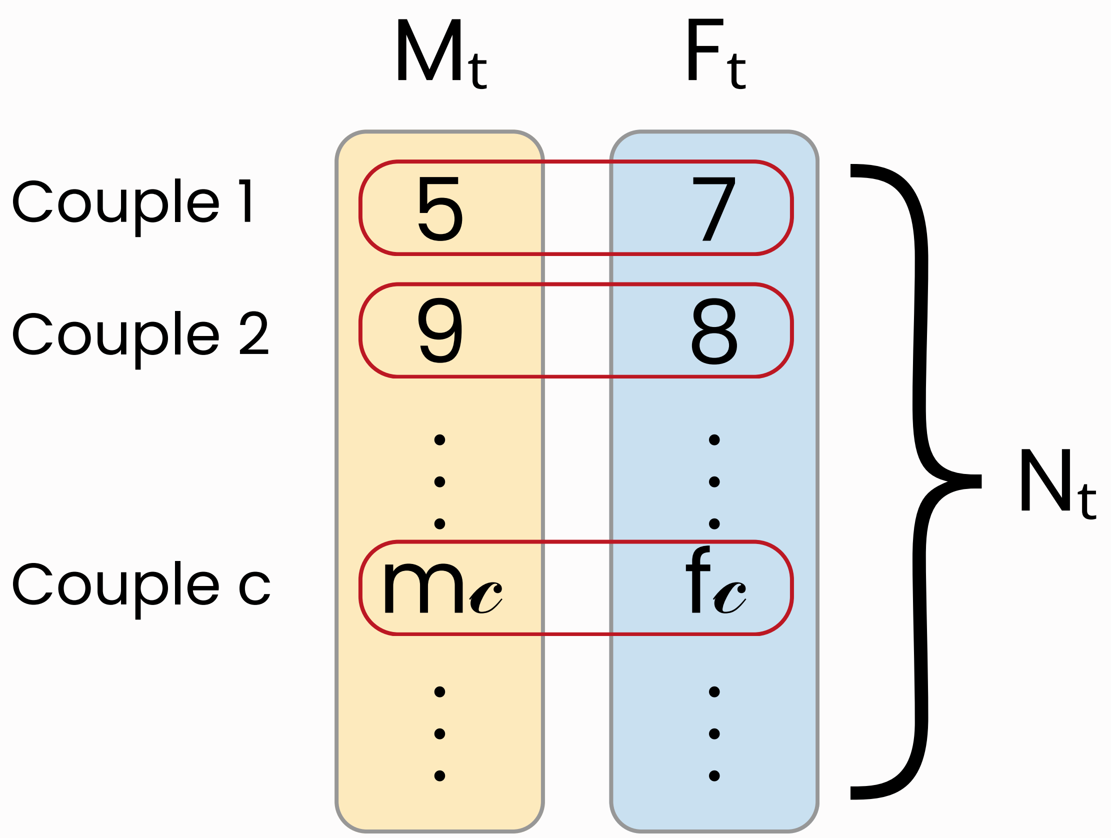
Model time t

Percentage of agents that are in a couple. Denoting as N_t the number of couples $t=N_t/N$.
Time grows from 0 to 100 with iterations

Correlation coefficient r

- M_t and F_t the vectors of male and female attractiveness in couples formed up to time t
- C_t list of all couples
- m_c and f_c male and female attractiveness in couple c

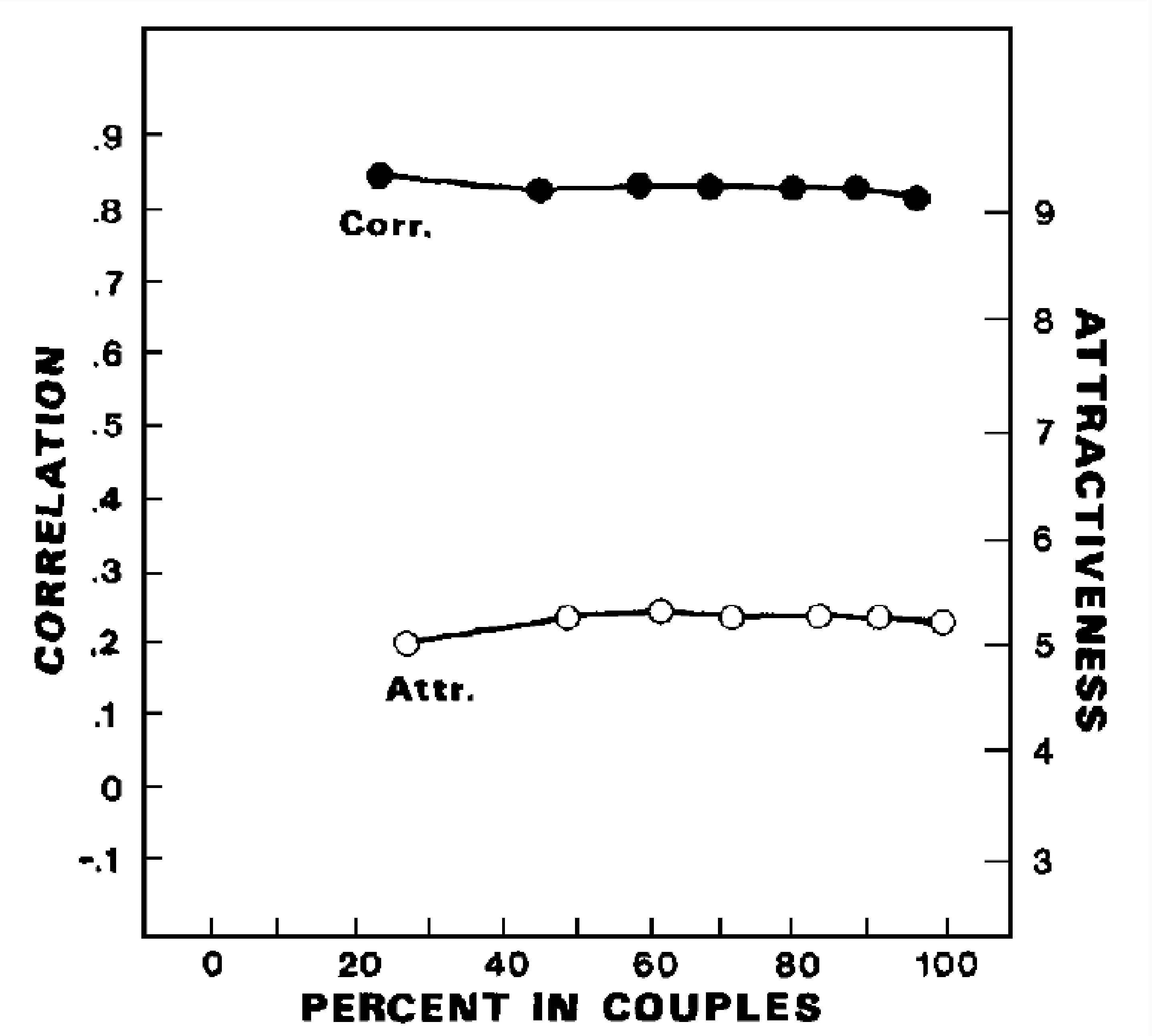
$$r(t) = r(M_t, F_t) = \frac{\sum_{c \in C_t} \left(m_c - \mu_M^{(t)}\right)\left(f_c - \mu_F^{(t)}\right)}{\sqrt{\sum_{c \in C_t} \left(m_c - \mu_M^{(t)}\right)^2 \left(f_c - \mu_F^{(t)}\right)^2}}$$



Mean attractiveness μ

$$\mu^{(t)} = \mu_M^{(t)} + \mu_F^{(t)} = \sum_{c \in C_t} \frac{m_c + f_c}{N_t}$$

Seeking **Similar** Match



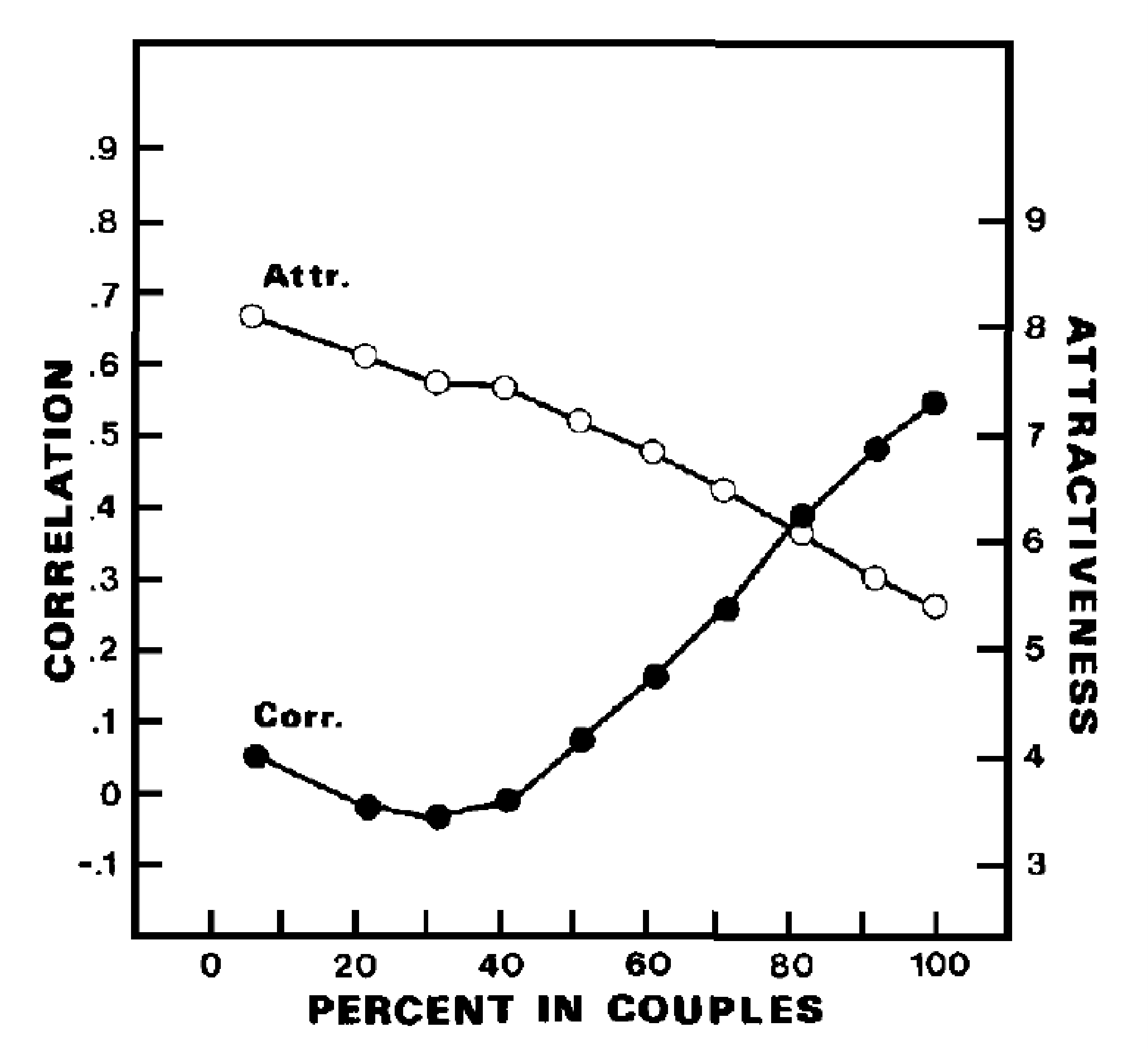
Outcomes over simulation time for the case of **seeking similar partners**:

- Correlation starts and stays very high (0.8)
- There is no real trend in correlation
- Mean couple attractiveness is around the average the whole simulation

Seeking Attractive Match

Outcomes over simulation time for the case of **seeking attractive partners**:

- Correlation starts low but raises pretty up to about 0.55
- Mean couple attractiveness starts much above average and approaches average
- Attractive agents couple earlier



What did we learn?

Main Result. Attractiveness matching is not necessary for observed correlations, they can be produced by attractiveness seeking alone.
Micro-Macro Gap. ABM reconciles apparently conflicting empirical results
Comparison with empirical data. Observed empirical correlation is closer to 0.55 than to 0.9. However this is not a strong evidence.

There are many simplifications, don't draw conclusions!

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

Conclusions

Emergence of Complex Social Behavior

- Humans behave differently in groups as in isolation: collective behavior emerges spontaneously
- Interdisciplinary approach to explain macro dynamics from micro behavior: physics/computer science is the link

Agent-Based Modelling (ABM)

- A computational approach to formalize and analyze social systems
- Agent properties and model objectives and assumptions

ABM Example: Date Choice Model

- Mismatch in empirical results: observations contradict experiments
- A simple model shows that seeking attractiveness in a finite dating pool also generates the observed correlations in couples