Agent-based modeling for social scientists

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MZES Social Science Data Lab
November 16 2022

Overview

What are ABMs?

Modeling

- Modeling: one creates a simplified representation of social reality that serves to express as clearly as possible the way in which one believes that reality operates (Gilbert 2020).
- Everyone is a modeler. The only question is whether implicitly or explicitly (Epstein 2008).

Meadows (2009, p. 86)

Everything we think we know about the world is a model. Every word and every language is a model. All maps and statistics, books and databases, equations and computer programs are models. [...] None of these is or ever will be the real world

Explicitly (formally) modeling has advantages for science, e.g.:

- Clarity of assumptions and deductions
- Precision
- Unimaginable outcomes

Agent-based models: Definition

Casini and Manzo (2016, p. 15).

An agent-based model is "a computer program designed to formally represent a set of hypotheses and executed to deduce, in a numerical form, the logical implications of such hypotheses. The computer program is of a particular kind, however"

What is particular?

→ Agent perspective: Bottom-up modelling of system by means of micro-level agents

Basic Assumptions

Agents are...(Macy and Willer 2002, Gilbert 2020)

1. Autonomous
2. Interdependent
3. Adaptive and backward-looking (memory, learning)
4. Potentially heterogeneous in attributes

Agents perceive their environment and/or other actors.
Agents interact with their environment and/or other actors.

Other types of models

- Structural equation models (e.g. regressions)
- Difference or differential equations
- Microsimulation: tracing macro changes in a population of isolated individuals
- Cellular automata

Flache and Macy (2011, p. 261)

"Structural equations and system-dynamics models, even with longitudinal data, are not sufficient, because they tell us only about the interactions among the attributes of the actors but not the actors themselves, who are typically assumed to be fully independent. Nor are game-theoretic models sufficient, because the Nash equilibrium only explains why a population pattern persists, and not how it obtains or changes."

Goals of ABMs

In ascending order of required empirical realism:

- Toy models: highly stylised abstract thought experiments
- Explanation: as a tool for theory building
- Causal inference (in-silico experiments)
- Prediction

ABMs used to be more concerned with theoretical development and explanation than with prediction.

Simple models with counter-intuitive results are often more credible because it can be explained. But they suffer from limited external validity.

ABMs and causal inference

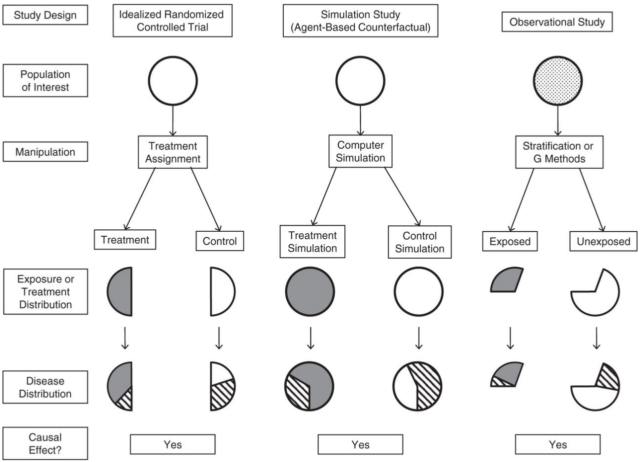


Figure 1: ABMs and causal inference (*Figure taken from Marshall and Galea 2015, p. 94*)

Software

Almost every programming language can be used for ABMs but these are some more widely used languages and packages.

- NetLogo (has an interface to R via package RNetlogo)
- Java/Kotlin (MASON)
- Python (MESA, agentpy)
- Julia

ABMs are most commonly implemented via **object-oriented programming**: a type of agent is a class and an individual agent is an object (Gilbert 2020).

ABMs and Social Science

The founding fathers have spoken

Emile Durkheim (1982, p. 86)

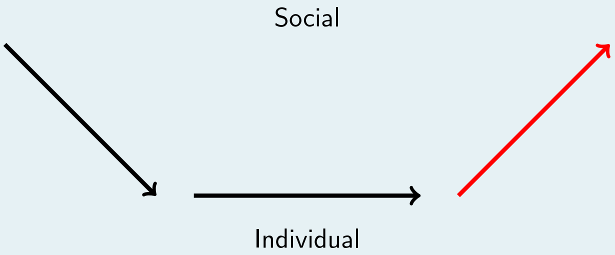
"[S]ociety is not the mere sum of individuals, but the system formed by their association represents a specific reality which has its own characteristics.

Undoubtedly no collective entity can be produced if there are no individual consciousnesses: this is a necessary but not a sufficient condition. In addition, these consciousnesses must be associated and combined, but combined in a certain way.

It is from this combination that social life arises and consequently it is this combination which explains it. By aggregating together [...] individuals give birth to [...] a psychical individuality of a new kind."

Emergence as a fundamental concept of and reason for the establishment of sociology!

Coleman (1990)



ABMs are a tool specifically designed to model emergence and tackle the micro-macro problem!

Social Complexity

Interest in ABMs reflects growing interest in the possibility that human behaviour, may be...

- Highly complex
- Nonlinear
- Path-dependent
- Adaptive
- Self-organizing
- Stochastic.

Social complexity: social dynamics as emergent properties of local interactions among adaptive agents who influence one another in response to the influence they receive, thereby often creating feedback loops.

ABMs do not solve everything

As always:

- For a scientific explanation, it is necessary but insufficient for a model to generate a social pattern:
- There are often multiple possible explanations
  $\rightarrow$ empirical hypothesis testing.
- Trade-off between realism of assumptions and traceability for the respective goal.

Flache and Macy (2011, p. 262)

"In sum, the ability to generate a population pattern from the bottom up is a necessary step, but it is not sufficient. The most we can say is that ABC models can take us well beyond what we can know using discursive models based on theoretical intuition or statistical models of interactions among variables or mathematical models of interactions in a static equilibrium."

Applications of ABMs in the social sciences

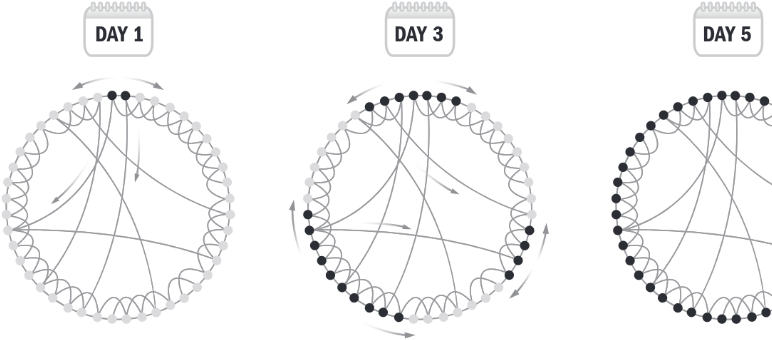
ABMs are already (relatively) commonly used in substantial fields as (for example):

- Sociology
    - Network creation, segregation, homophily
    - Diffusion of informations, innovations, disease (in networks)...
    - Social influence, institutions, norms
- Political science
    - Opinion dynamics and polarisation
    - Party competition
- Economics
    - N-person games and evolutionary game theory (collective action and cooperation)
    - Stock market models and financial crises
    - Industrial networks and supply chains

Examples

Example I: Forgetting in simple and complex contagions

- Information can travel through human networks via "word of mouth"
- Human networks are typically *small-world networks*:
- They are locally clustered with bridging ties
- Therefore, information can diffuse through a population very fast

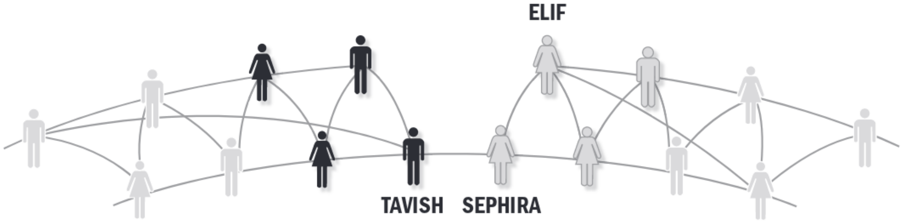


Complex contagions

But for high-stake information and behaviour, diffusion speed is rather slow...?

A possible explanation (Centola and Macy 2007):

- Humans only believe the information if *at least two* others tell it.
- High-stake information and behaviours therefore spreads more slowly
- And cannot take advantage of the bridging ties.
- The information can be trapped in subnetworks if the bridges do not have sufficient *width*.



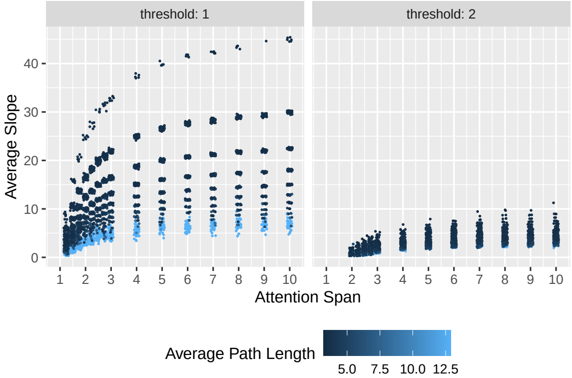
How does forgetting affect diffusion?

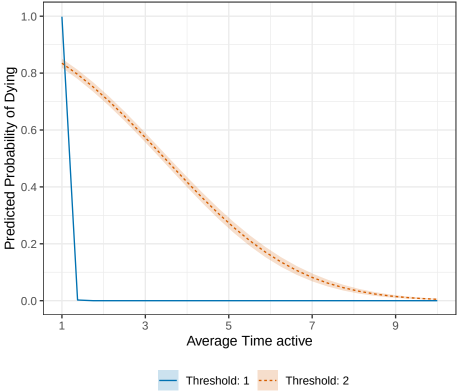
- Not everyone who heard the information remembers it.
- Therefore, it is not guaranteed that the entire population knows it at any time.
- We can model the proportion a of the population knowing the information at time t as a differential equation:
  $\partial a(t)/\partial t = P(transmitting)\ a(t)(1 - a(t)) - P(forgetting)\ a(t)$
- There is an inner equilibrium at $1 - \frac{P(forgetting)}{P(transmitting)}$

ODEs like this assume a deterministic process, simple contagions and random networks though...

Let's have a look at this as a **stochastic process on small-world networks** in NetLogo!

Simulation results





Summary: Forgetting in simple and complex contagions

- If the contagion survives, it eventually oscillates around the analytical equilibrium, no matter if simple or complex.
- Simple contagions spread fast, complex contagions slow.
- Due to their slower speed, complex contagions die much more likely than simple contagions.
- Up to a critical mass, information can die out by random chance.

Example II: a socio-economic model of the housing market

There are spatial inequalities within cities concerning...

- social and economic characteristics of residents
- and housing quality.

And these inequalities are...

- highly correlated and
- very stable over time
- but when they change, it is rapid and locally isolated.

Motivation

But currently we only have separate theories concerned with

- social and economic segregation,
- gentrification and
- neighbourhood decay

although they are clearly part of the same complex (sub-)system.

In my dissertation, I try to build a unified model of the housing market by treating decisions in the housing market as **economic decisions with spatial constraints**.

Starting points:

- Benard and Willer (2007)
- Microeconomic Theory

Bernard and Willer (2007)

Bernard and Willer (2007): A wealth and status-based model of residential segregation

- Inhabitants of a city have two characteristics, their social status and wealth.
- Status and wealth can correlate.
- They want to live next to high-status others.
- Housing prices can be random or influenced by the average wealth of neighbours.
- $\rightarrow$ interaction of correlation of wealth and status and price endogeneity in producing social and economic residential segregation.

To get a feel how this looks like, lets go to NetLogo.

Outline of my model

Schelling-type model inhabited by two types of actors:

- Households demanding housing characterised by their
  - wealth w_i and
  - social milieu s_i
  - which can be set to correlate (parameter r).
- Landlords supplying housing.
  - Fixed number of housing units (short-term inelasticity)
  - Landlords supply housing *quality*.

Demand

Assumptions

1. Households prefer a higher quality q_m of their location m.
2. Households prefer to live near socially similar others.

Households maximise the utility provided by a housing unit m from the budget set.

$$U_i(m) = (1-a)q_m - \frac{a}{n_m}\sum_{j=1}^{n_m}(s_{mj} - s_i)^2$$

Parameter $a \in [0,1]$: how important are neighbours?

Supply

Landlords aim to maximise residents wealth.

Uncertainty Problem

Landlords cannot know future development of their neighbourhood and therefore attractiveness of their housing unit.

Solutions:

1. learning from past experience and/or
2. learning from relevant others (neighbours).

The specifics are still work in progress.

Summary: a socio-economic model of the housing market

I model the housing market as a complex system in which...

- households change each others budget sets and utilities.
- landlords compete for residents' wealth.
- landlords influence each other on whether to invest.

After model building, I am going to test the model classically via empirical implications of the theoretical model.

Example III: Dynamic models of multiparty competition

- Politics in democratic societies is characterized by (multi)party competition
  - Multiparty competition: More than two parties compete for voters' support
- Multiparty competition is a complex dynamic system
- How to model dynamic multiparty competition?
  - Classical formal analysis (e.g., game theory) $\rightarrow$ analytical intractability
  - Seminal agent-based model of dynamic multiparty competition established by Laver and Sergenti (2011) **(see also, e.g., Laver 2005; Lehrer and Schumacher 2018)**
    - Considers dynamic nature of party competition
    - Allows realistic behavioral assumptions

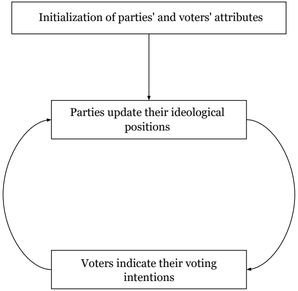


Figure 2: Schematic illustration: agent-based model of dynamic multiparty competition (*author's own illustration*).

My work

- Work I present here builds on the agent-based model of Laver and Sergenti (2011)
- Research question: What are the short-term effects of *cordons sanitaires* vis-à-vis radical parties on voting behavior in dynamic multiparty competition?
  - Mainstream parties erect a *cordon sanitaire* vis-à-vis a radical party when they publicly announce during the campaign that they will not form a coalition government with the radical party
- Existing research: Micro-level theoretical knowledge about how *cordon sanitaires* shape individual voting decisions (e.g., Bahnsen, Gschwend and Stoetzer 2020; Gschwend, Meffert and Stoetzer 2017)
- Challenge: Implications of this theoretical knowledge on parties' vote share in dynamic multiparty competition far from obvious!
- Approach: Assess effect of *cordon sanitaires* via systematic what-if thought experiments with an agent-based model of dynamic multiparty competition

Using the in-silico laboratory of counterfactual agent-based simulations

- Why agent-based modelling?
  - Agent perspective allows to integrate theoretical micro-level knowledge about how *cordon sanitaires* shape individual voting decisions
  - Acknowledges dynamic nature of party competition
  - Realistic behavioural assumptions about parties and voters
  - Flexibility of the approach allows considering peculiarities of specific party systems
- Agent-based model as a in-silico laboratory in which implications of theoretical knowledge are rigorously examined

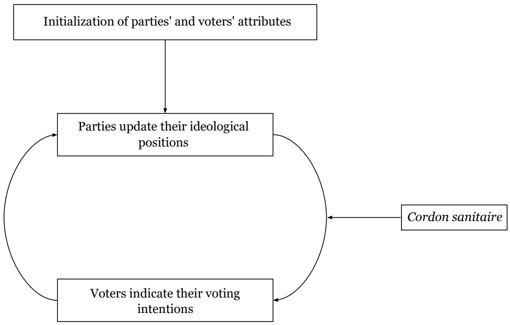


Figure 3: Schematic illustration: my agent-based model of dynamic multiparty competition (*author's own illustration*).

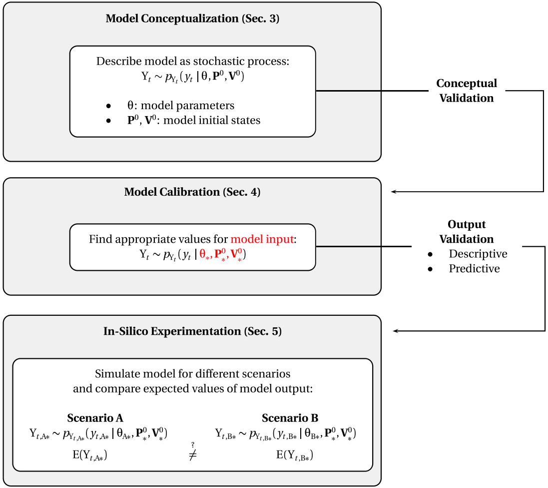


Figure 4: Roadmap (*author's own illustration*).

Model conceptualization

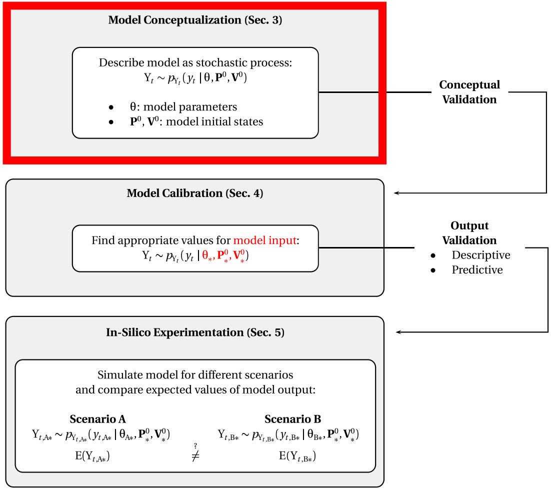


Figure 5: Roadmap (*author's own illustration*).

Model conceptualization: Interacting parties and voters

- Setup:
  - Parties and voters are placed in a two-dimensional ideological space
- Dynamics:
  - Parties update ideological positions according to different heuristics in light of voter support
  - Voters indicate voting intentions in light of parties' ideological positions
- Coalition-directed voting instead of proximity voting (contrast to Laver and Sergenti 2011)
  - Coalition-directed utility function:

$$u_t^i(j) = -\beta\left(\sum_{n=1}^{N_{c_j}} \|(x^i, y^i) - (Z_t^{c_j n, x}, Z_t^{c_j n, y})\|_2^2 \gamma_t^{c_j n}\right) - (1-\beta)(\|(x^i, y^i) - (p_t^{j,x}, p_t^{j,y})\|_2^2)$$

- *Cordons sanitaires* affect coalition expectations following Bahnsen, Gschwend and Stoetzer (2020)

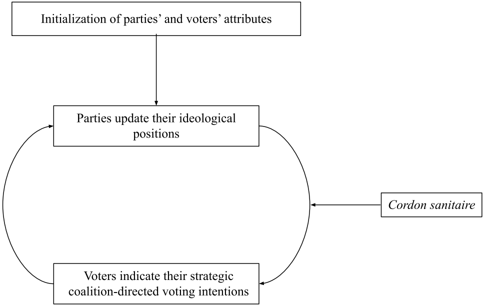


Figure 6: Schematic illustration: my agent-based model of dynamic multiparty competition (*author's own illustration*).

Model conceptualization

- Model is a Markov Chain, i.e. a sequence of random variables $X_0, \ldots, X_T$ that satisfy the Markov property: $X_t \sim p_{X_t}(x_t \mid \theta, \mathbf{P}_0, \mathbf{V}_0)$ with model input being θ, $\mathbf{P}_0$, and $\mathbf{V}_0$
  - θ: model parameters
    - Including model parameter indicating whether *cordon sanitaire* is intact against certain party
  - $\mathbf{P}_0$ and $\mathbf{V}_0$: initial states
- Model description also by means of *ODD protocol* **(Grimm et al. 2020)**
- Programming in `R` and `NetLogo`

Conceptual validation

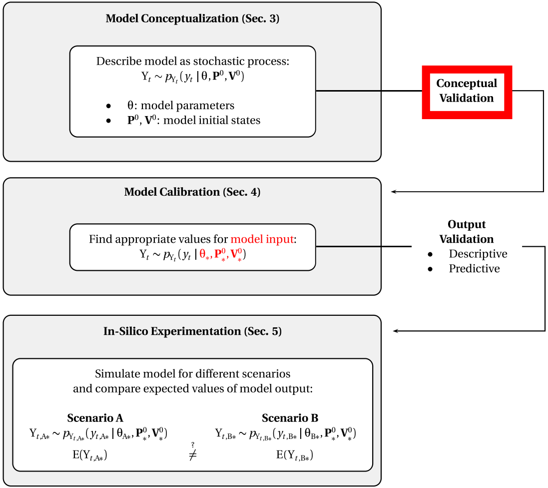


Figure 7: Roadmap (*author's own illustration*).

Model Calibration

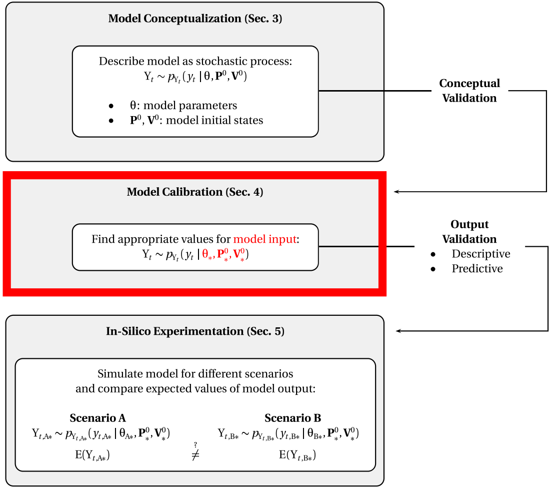


Figure 8: Roadmap (*author's own illustration*).

Model calibration

- Finding such values for the model inputs that make the model output resemble a specific party system
  - Interesting case: 1930s Weimar Republic in which government takeover by the radical right (NSDAP) had devastating implications
  - Calibration aim: Find input values that make the model output look like the Weimar party system of 1930 at time $t = 0$ and like the Weimar party system of 1932 at time $t = E > 0$
- Historical data: Vote shares (Falter et al. 1986) and proxies for historical ideological positions (Hansen and Debus 2012)

1. Calibration using directly observable real-world equivalents
2. Rigorous calibration
   - Global sensitivity analysis: Sobol method (e.g., Saltelli et al. 2008)
   - Approximate Bayesian computation (Prichard et al. 1999)

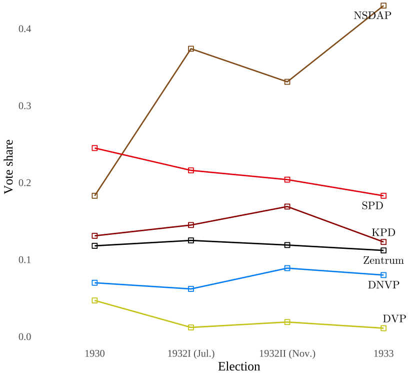


Figure 9: Party vote shares in the 1930s Weimar Republic (*author's own illustration*).

Overview of model inputs

Input type	Input	Description	Calibration strategy
	N	Number of parties	Direct observation
	$p_0^{j,x}$	Id. position (x-dimension) of party j, $t = 0$	Direct observation
	$p_0^{j,y}$	Id. position (y-dimension) of party j, $t = 0$	Direct observation
Initial states	$p_0^{j,r}$	Decision heuristic of party j (time-invariant)	Approximate Bayesian computation
	$p_0^{j,cs}$	*Cordon sanitaire* vis-à-vis party j? (time-invariant)	Direct observation
	v_0^j	Vote share of party j, $t = 0$	Direct observation
	V^1	Size of subpopulation 1	Approximate Bayesian computation
	V^2	Size of subpopulation 2	Fixed without loss of generality
	$m^{1,x}$	Mean (x-dimension) of subpopulation 1	Approximate Bayesian computation
	$m^{2,x}$	Mean (x-dimension) of subpopulation 2	Approximate Bayesian computation
	$m^{1,y}$	Mean (y-dimension) of subpopulation 1	Approximate Bayesian computation
Parameters	$m^{2,y}$	Mean (y-dimension) of subpopulation 2	Approximate Bayesian computation
	sd	Standard deviation of subpopulations	Approximate Bayesian computation
	E	Time tick of the second election	Fixed, non-influential according to Sobol method
	β	Weight of coalition-directed considerations	Approximate Bayesian computation
	h	Coalition relevance threshold	Fixed, non-influential according to Sobol method

Table 1: Overview of the model inputs

Identifying non-influential inputs: Global sensitivity analysis (Sobol method)

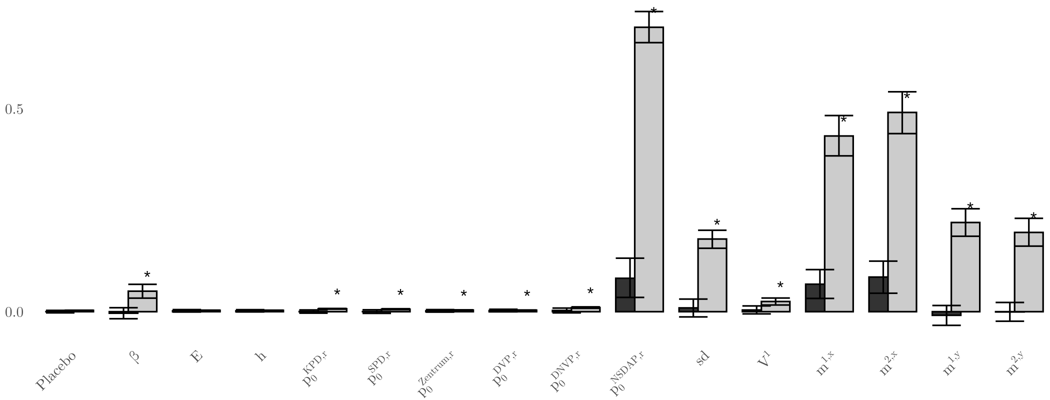


Figure 10: Sobol first-order and total-order sensitivity indices for model inputs.

Approximate Bayesian computation for influential inputs

- Define a multivariate prior distribution of inputs
- Draw inputs from prior, simulate data for these inputs and keep inputs that result in small difference between simulated and observed data
  - Define a measure to assess the difference between simulated and observed data
  - Determine a tolerance level for which the ABC procedure satisfies the *coverage property*
- Series of robustness checks
  - More computational power
  - Slightly different tolerance levels
  - Alternative party position proxies

Approximate Bayesian computation for influential inputs

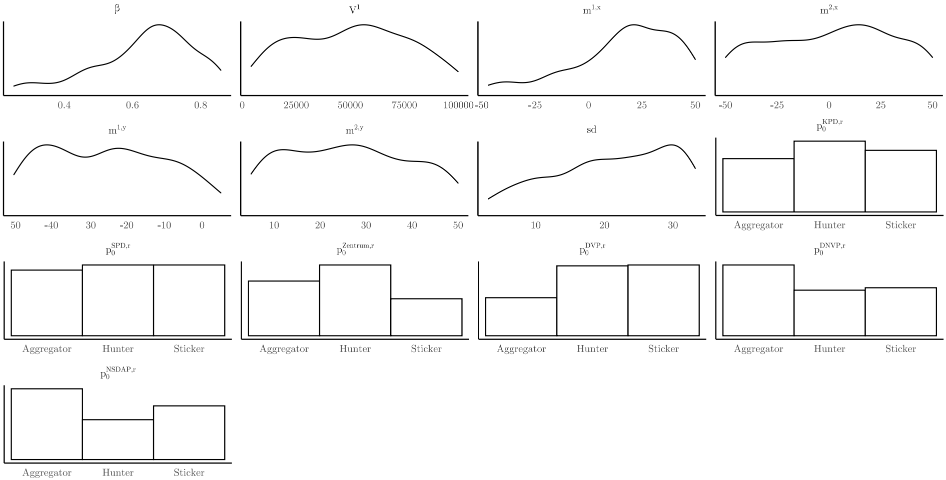


Figure 11: Marginal posterior distributions of inputs.

Output validation

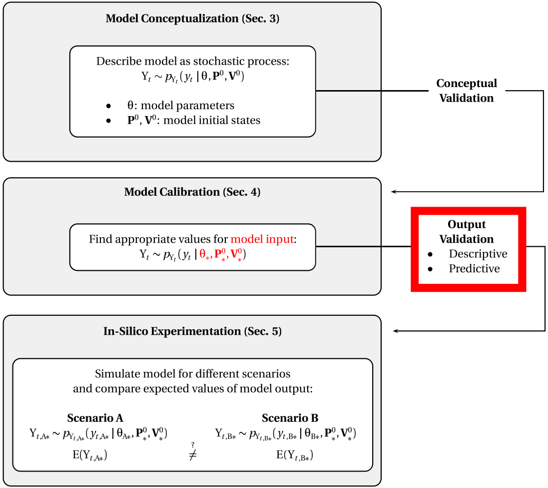


Figure 12: Roadmap (*author's own illustration*).

Output validation

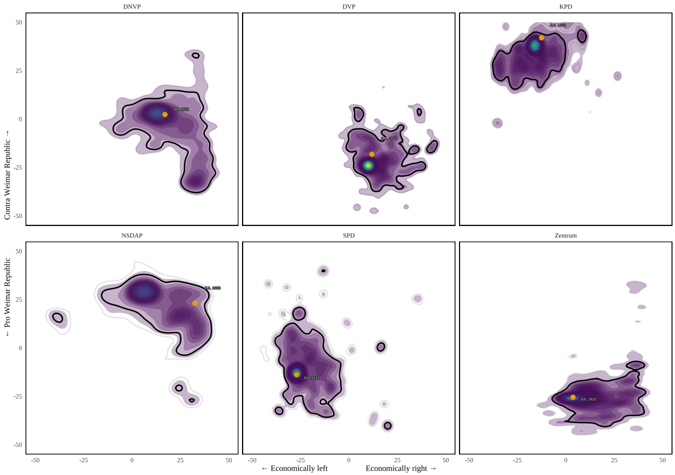


Figure 13: Predicted ideological positions of parties for the July 1932 election in the artificial 1930s Weimar Republic (purple) and actual positions (yellow).

Model Conceptualization (Sec. 3)

Describe model as stochastic process:
$Y_t \sim p_{Y_t}(y_t \mid \theta, \mathbf{P}^0, \mathbf{V}^0)$

- θ: model parameters
- $\mathbf{P}^0, \mathbf{V}^0$: model initial states

Conceptual Validation

Model Calibration (Sec. 4)

Find appropriate values for model input:
$Y_t \sim p_{Y_t}(y_t \mid \theta_*, \mathbf{P}^0_*, \mathbf{V}^0_*)$

Output Validation

- Descriptive
- Predictive

In-Silico Experimentation (Sec. 5)

Simulate model for different scenarios
and compare expected values of model output:

Scenario A		**Scenario B**
$Y_{t,A*} \sim p_{Y_{t,A*}}(y_{t,A*} \mid \theta_{A*}, \mathbf{P}^0_*, \mathbf{V}^0_*)$		$Y_{t,B*} \sim p_{Y_{t,B*}}(y_{t,B*} \mid \theta_{B*}, \mathbf{P}^0_*, \mathbf{V}^0_*)$
$E(Y_{t,A*})$	$\overset{?}{\neq}$	$E(Y_{t,B*})$

In-silico experimentation

- What are the short-term effects of a *cordon sanitaire* vis-à-vis the NSDAP on the electoral success of the artificial NSDAP?
- Experimental design: Compare two artificial 1930s Weimar democracies
  - In one artificial 1930s Weimar Republic the NSDAP faces a *cordon sanitaire*
  - In the other artificial 1930s Weimar Republic the NSDAP does not face a *cordon sanitaire*
- Note again: Results of the in-silico experiments reflect the logical theoretical implications of the implemented micro-level knowledge → systematic what-if thought experiment

Results: In-silico experimentation

Figure 14: Effect of the *cordon sanitaire* on NSDAP vote share.

Results: Additional analyses (example I)

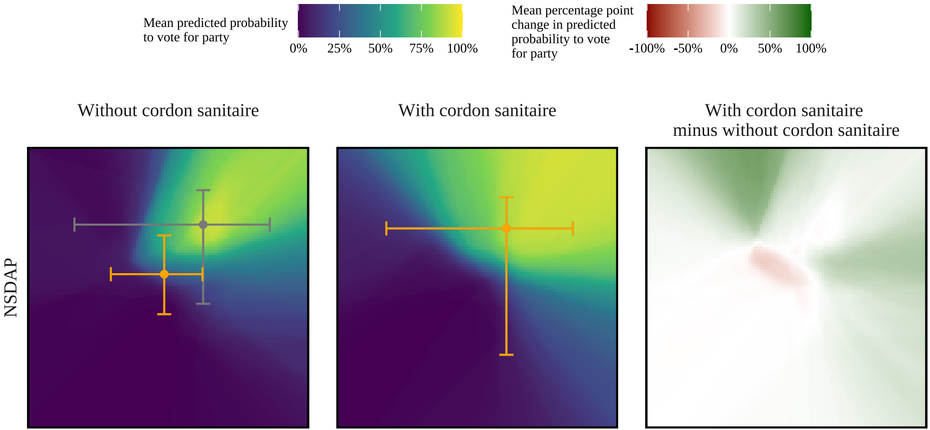


Figure 15: Individual voting decisions by ideological position of voters with and without *cordon sanitaire*.

Results: Additional analyses (example II)

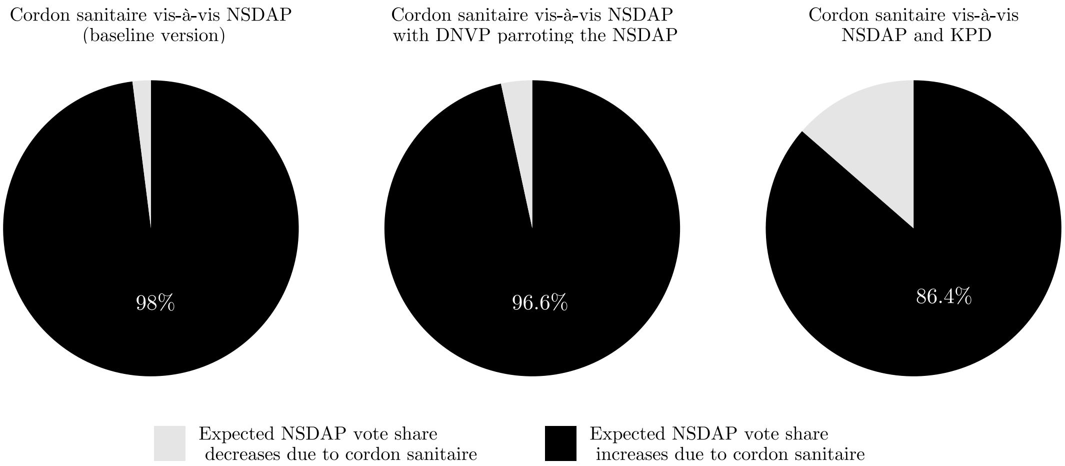


Figure 16: Effect of alternative *cordon sanitaire* designs on NSDAP vote share at the 1932I election.

Conclusion

- Substantial lessons learned
  - Under reasonable and mild assumptions, existing theoretical knowledge can predict that a *cordon sanitare* vis-vis a radical party boosts the electoral support of a radical party in the short-term
  - Illustrates the theoretical possibility that *cordons sanitaires* can achieve the opposite of what they intend
  - Calls for theoretical and empirical investigation of conditions under which *cordons sanitaires* actually reduce radical parties' electoral success
- Methodological lessons learned: state-of-the-art agent-based modelling for polsci
  - High computational demand (way more than 100 GB of simulated data in the course of calibration and in-silico experimentation)
  - Calibration (and validation) of agent-based models is an open and rapidly evolving area of research $\rightarrow$ Sobol method and approximate Bayesian computation promising
  - Uncertainty about the values of model inputs are rarely acknowledged during in-silico experimentation $\rightarrow$ acknowledge two sources of uncertainty: *input uncertainty* and *random component uncertainty*

Summary

Summary

- ABMs are computer programs consisting of agents with behavioural rules embedded in an environment.
- These agents are typically autonomous, interdependent, adaptive and heterogeneous in attributes.
- The program can then be used to deduce macro-level implications of the behaviour of agents at the micro-level.
- ABMs are very flexible and allow a wide range of research goals, from simple thought experiments to forecasting.
- ABMs are therefore a tool to model emergence and directly tackle the micro-macro problem abundant in social science.
- They allow for a stochastic, dynamic and networked view on social/political phenomena.

Benefits and outlook

- Method to deal with issues that you cannot manipulate experimentally or easily observe.
- Relaxing assumptions (e.g., introducing bounded rationality) but still formalisable.
- Hard to formalise social science mathematically and often no analytical solution.

Our hopes and likely future developments

- Calibration will likely gain much more importance and methodological attention
- Prediction and evaluation of policies (e.g., COVID-19)
- ABM might be a framework to achieve theoretical synthesis and to unify existing theories

Recommended Literature

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Thank you for your attention!

We look forward to questions and comments

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